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Towards next-generation energy planning decision-making: An expert-based framework for intelligent decision support

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ABSTRACT

Achieving sustainable energy planning and development involves complex decision-making processes. The energy planning decision-making (EPDM) field relies on a plethora of decision analysis methods that offered many solutions to process a variety of energy management and strategic decision-making problems. However, current EPDM solutions are unable to overcome the increasing complexity of strategic energy planning situations involving a large number of stakeholders in uncertain, dynamic, and distributed environments. This raises significant new challenges for researchers in both decision sciences and renewable and sustainable energy planning. On the basis of a representative assortment of peer-reviewed related literature selected by querying multiple electronic databases and indexed in *Scopus* and *Web of Science* databases domain journals over the last 12 years, this paper exhaustively highlights and discusses limitations of existing strategic EPDM solutions. The analysis is based on a classification specially developed by holistically harmonizing important domain concepts to categorize the considered representative sample of the field of interest. Additionally, this paper integrates results and conclusions from some recent and most cited literature reviews to (i) formulate essential evidence as well as practical and conclusive literature's support– alongside with the formulated representative sample –to this paper's subsequent insights and statements, and (ii) guarantee that no relevant articles have been excluded. A total of 78 related works is gathered and analyzed to provide a general view and discussion on major complexities found in classical/traditional strategic EPDM solutions and challenges for next-generation EPDM solutions. Moreover, a comparative analysis of the two solutions and a set of “quality indexes” of a next-generation EPDM solution were identified and some proposals were made to improve future applicative research. As an original result coming from the “quality indexes” identified through the review process, an intelligent expert-based framework for next-generation EPDM solutions is developed for enhanced renewable and sustainable energy planning.

1. Introduction

Energy has been the central element of the wide-ranging concepts of sustainability during the last 40 years [1,2]. In this respect, efficient, clean, and renewable energy has been distinguished as the key solution to enable a sustainable vision for future life. The last two decades have witnessed a significant increase in the use of renewable energy sources (RES) to ensure a more efficient and sustainable environment [3,4].

Despite their paramount advantages, RES also present notable drawbacks, such as their reliance on climate to generate energy, hence their exploitation requires complex design, planning, and effective optimization methods [5]. In this sense, a common concern in the energy sector pertains the consideration of pre-defined constraints (e.g., changes in the organization of energy markets, prevalent uncertainty within energy scenarios, conflicting views of several stakeholders, etc.) when answering strategic questions or making operational decisions [6]. A variety of (multi-objective) optimization techni-

Abbreviation: AI, Artificial intelligence; ANN, Artificial neural network; BI, Business intelligence; BN, Bayesian network; CRP, Consensus reaching process; DBMS, Database management system; DSS, Decision support system; DGMS, Dialogue generation management system; EIS, executive information system; EPDM, Energy planning decision-making; ES, Expert system; FMCDM, Fuzzy-based multiple criteria decision-making; GDM, Group decision-making; GIS, Geographic information system; ICT, Information and communication technology; IS, Information system; IDSS, Intelligent decision support system; KBMS, Knowledge base management system; LCA, Life cycle assessment; ML, Machine learning; MBMS, Model base management system; MCA, Multiple criteria analysis; MCDM, multiple criteria decision-making; MOO, Multi-objective optimization; RES, Renewable energy sources

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Table 1
Categories of EPDM and examples of decisions to be made.

Decision level	Category	Examples
DL.1. Strategic	C1.1. Energy planning	Regional [18,22,24,26,61,62], local [19,30,63,64–67], urban [68–70], rural [71–77]
	C1.2. Energy policy	Planning [37,78,79], evaluation [43,52,80,81], frameworks [82,83]
	C1.3. Environmental impact analysis	Environmental and ecological decision-making [84–86], life-cycle assessment [2,87]
	C1.4. Energy evaluation and assessment	Investments [88–91], sustainability assessment of energy systems [38,92-95], sources, technologies and options [12,13,15,28,35,39,94,96–98], power expansion alternatives [99–101], plants [47,102], power generation scenarios [103,104], production pathways [25,86,105]
	C1.5. Site selection	Projects and platforms [45,106–109], plants [4,14,110], power stations [111], power generation farms [46,112–117]
DL.2. Operational	C2.1. Operational planning	Distributed generation planning [69,118–123], energy efficiency [124–129], energy demand [130]
	C2.2. Energy management	Energy balancing and storage [131–135], demand side and smart management [27,32,136–141], energy-saving [3,142–146], maintenance, monitoring, faults-detection, and diagnostics [147–153], smart buildings, grids, and cities [154–159]

ques [5–8], have been previously used to provide a desirable energy resource allocation, and enable energy-safe capacity expansion plans with minimized costs and maximized system's reliability.

Notwithstanding, energy optimization is only part of an overall energy planning decision-making (EPDM) field that relies on a plethora of decision analysis methods [9]. These methods allow policy planners and decision makers to process a variety of renewable and sustainable energy planning situations. On the one hand, such situations can be formally defined as collections of complex energy management and decision-making problems, characterized by [10,11,1,12]: (i) inherent features and multiple participants; (ii) a set of possible alternatives evaluated from multiple perspectives, criteria, and sub-criteria; (iii) the need for attaining mutual compromise among decision makers' preferences; (iv) analysis in realistic scenarios involving negotiation. On the other hand, each EPDM process needs to consider evaluating social, technical, economic, environmental, and political energy aspects across time, space, and scenarios, while striking a balance between the stakeholders' priorities, nature preservation, and societal welfare [13,14].

The presence of conflicting objectives in EPDM processes due to (a large number of) involved stakeholders with different aims and preferences [15,16] further complicate the decision-making process. To overcome these complexities, hence improving strategic and operational energy planning, a great abundance of research has been devoted since the 1960s to EPDM solutions through developing standalone decision-making models or implementing different computerized tools such as decision support systems (DSSs) and expert systems (ESs) [17–32]. Firstly, single criterion decision-making models are deemed insufficient to incorporate energy considerations from multiple perspectives, simultaneously [6,33]. As a result, multiple criteria analysis (MCA) has gained an important place in a vast range of EPDM situations such as the assessment of renewable energy technologies and policies [6,10,11,34]. However, RES exploitation often requires dealing with increasing complexity to manage projects, rapid energy market changes, as well as unknown climate conditions. Additionally, it is time-sensitive due to uncertainty inherent in short and long-term planning decisions (for instance, whether and how a power plant will operate during the next 25 years) [15]. Moreover, EPDM requires handling uncertainty inherent to stakeholders' judgments, which are often subject to imprecision. The involved stakeholders often express difficulties to provide precise assessments when evaluating alternatives according to criteria. This is further complicated in multiple stakeholders' environments due to the different levels of knowledge, resulting in biased decisions [4,15,35]. Fuzzy set theory was introduced by Zadeh [36] in [36] as an effective instrument to facilitate decision-making situations in vague and ambiguous contexts. DSSs that utilize fuzzy decision models have been proposed to tackle various EPDM situations [30,37–41], by effectively exploiting subjective judgments under multiple perspectives. In particular, numerous studies combine traditional multiple criteria decision-making (MCDM) methods and fuzzy models resulting in fuzzy-based MCDM (FMCDM) approaches to model both qualitative and quantitative factors and to overcome the limitations that arose when used separately [13–15,34,35,42–47].

Nevertheless, existing EPDM solutions usually provide final decisions or recommended actions without deeply examining the relationship between those solutions and the existing decision parameters (participants, alternatives, and criteria). Therefore, they are not "intelligent" enough to: (i) identify and analyze the relationships between initial inputs, participants profiles, and obtained outputs, (ii) provide logical interpretations and rational assumptions from the outputs, and (iii) extract additional knowledge from the decision-making process. These solutions are, by contrast, completely data-driven (i.e. sufficiently sample data are required to estimate the final decisions) [48]. Moreover, the sophistication and widespread use of electronic and smart devices, such as mobile phones and tablet computers, and the advent of Web technologies and services, particularly when cloud-enabled, suggest that a next-generation EPDM solution may not have to employ traditional computational models and user interfaces [49]. Thus, the right tools need to be offered to planners and decision makers (governments, investors, regulators, consumers, interest groups, etc.) to (i) perform detailed analysis, (ii) obtain balanced recommendations, and (iii) get computerized support in dynamic, complex, and uncertain EPDM environments [6].

Under the above scenario, the objective of this paper is to investigate complexities and challenges of EPDM solutions. Motivated by that, the main contribution of this study is threefold:

A literature review that surveys the major limitations of existing EPDM solutions. Given the magnitude of this research area, a comprehensive and complete review of *all* EPDM solutions is not possible. Instead, our efforts concentrate on describing representative scientific papers for various EPDM situations, excluding the operational decision level (see Table 1). The analysis was based on a classification specially developed to categorize the considered representative sample of the field of interest (strategic EPDM solutions) selected by querying multiple electronic databases indexed in *Scopus* and *Web of Science* databases domain peer-reviewed journals over the last 12 years.

Additionally, this paper integrates results and outcomes from some recent [1,2,6,50–56] and most cited literature reviews [5,9–11,39,57–60], to: (i) formulate essential evidence as well as practical and conclusive literature's support– alongside with the formulated representative sample –to this paper's subsequent insights and statements; and (ii) guarantee that no relevant articles have been excluded. Moreover, differences between previous literature reviews in this area of research and our proposed work are explained.

Whilst doing so, related works are gathered and analyzed to provide a general view and discussion on (i) major complexities found in classical/traditional strategic EPDM solutions, and (ii) challenges for next-generation EPDM solutions. Then, a comparative analysis of the two approaches and a set of "quality indexes" of a next-generation EPDM solution were identified and some proposals were made to improve future applicative research. As an original result coming from the "quality indexes" identified through the review process, an intelligent and expert-based framework for next-generation EPDM solutions is developed for enhanced renewable and sustainable energy planning.

This paper is organized as follows. In Section 2, we firstly present an overview, features, and main findings of related reviews, the research methodology used for conducting this review, and the proposed classification. The detailed in-depth analysis of selected papers, comparative analysis, along with proposed "quality indexes" are presented in Section 3. In Section 4, we propose an extended theoretical framework to overcome the limitations of current strategic EPDM literature. Finally, Section 5 summarizes the findings of this work and suggests some focal points for future research.

2. Materials and methods

An EPDM process consists of solving well-defined decision-making situations to fulfill the main objectives underlying energy planning at regional or national level. These processes usually take place at different decision levels (strategic or operational) and time frames (from long-term planning to near real-time control) [6]. Hence, it is convenient to firstly distinguish between these types of EPDM. Firstly, *strategic planning* consists of evaluating short and long-term sustainable actions of exploiting RES and technologies, future investments' appraisal and economic decisions, policies planning and global regulations considerations. Conversely, *operational planning* considers near real-time control and energy management operations. These operations require taking effective tactical and technical actions such as proposing improvements in existing energy projects, systems, and technologies (energy distribution, balance, storage, supply, and saving), maintenance, monitoring, faults-detection, or diagnostics. The most frequent EPDM categories reported in the literature are summarized in Table 1, along with examples of related literature within each category. It is worth pointing out that the proposed classification of EPDM problems is not the only possible one. Likewise, some of the investigated examples might belong to one or more categories since strategic and operational energy planning are both conflicting and complementary.

Due to the vastness of literature on this topic, which cannot be exhaustively reviewed, this paper concentrates on proposed solutions to address EPDM problems that belong to the first decision level's category (DL.1. Strategic). More precisely, the focus is herein placed on major limitations and challenges of strategic EPDM systems, models, and methods. Thus, this section presents the materials and methods used to overview previous strategic EPDM related work.

2.1. An overview of reviews on EPDM

The nature of problem-solving in EPDM has attracted extensive research interest since the end of the 1990s. In one of the first literature reviews focused on EPDM, Pohekar and Ramachandran [10] investigated the use of several MCDM methods related to renewable and sustainable energy planning. MCDM is an active discipline of operations research that investigates and defines tools for complex decision-making situations involving both quantitative and qualitative factors. Based on [10], multi-attribute utility theory (MAUT), analytic hierarchy process (AHP), analytic network process (ANP), preference ranking organization method for enrichment evaluations (PROMETHEE), elimination and choice expressing reality (ELECTRE), and fuzzy models were the most commonly used techniques for renewable and sustainable energy planning. In the same direction, Polatidis et al. [57] developed a methodological framework to provide insights regarding the suitability of MCDM techniques in the context of renewable and sustainable energy planning. They described major technical requirements for energy planning, the main MCA methods, and a comparative evaluation of existing techniques. Other reviews focused on investigating the use of MCA methods for different energy planning problems [9,11,58,59,160].

Another interesting review in this area of research is the one conducted by Baños et al. [5]. They proposed to investigate existing optimization methods to deal with RES drawbacks (e.g., the discontinuity of generation, as most RES depend on the climate). In their study, Baños et al. argue that continuous advances in computer hardware and software are opening the avenues to deal with optimization problems using computational resources in renewable and sustainable energy planning. Their work reviews state-of-the-art computational optimization methods applied to renewable and sustainable energy development, highlighting the latest advances in this field. Interesting research directions are raised in their work, such as the use of heuristic approaches, pareto-based multi-objective optimization (MOO), and parallel processing as promising research areas in the field of renewable and sustainable energy planning.

FMCDM approaches have been extensively studied for decision-making problems involving the choice of the optimal RES. Numerous literature reviews focused on the combined use of MCDM methods with fuzzy set-based models, hence Mardani et al. [60] systematically investigated methodologies and applications of

Table 2
A summary of most recent EPDM literature.

# Reference (Year)	Included articles	Period(s)	Review characteristics	Authors' summary of results	Authors' conclusions
R1 Strantzali and Aravossis [1]	183	1983–1994 1995–2004 2005–2014	*RC1*. A review of state-of-the-art decision support methods applied to renewable and sustainable energy planning. *RC2*. The review particularly investigates trends in the assessment of RES investments. *RC3*. A representative sample of studies published in the target research field are surveyed. *RC4*. The selected papers have been classified in terms of year of publication, decision-making technique, energy type, criteria utilized, application area(s) and geographical distribution.	*AR1*. The number of publications related to assessing RES investments tripled over the last decade. *AR2*. Most of the methods used are based on traditional approaches, with notable repercussions in the field of MCA. Related application areas include energy policy analysis, environmental impact analysis, technology choice and project appraisal. *AR3*. Life Cycle Assessment (LCA) and Cost Benefit Analysis (CBA) are decisive aspects in the fields of energy policy and management and environmental impact analysis, respectively. *AR4*. Two dominant trends with a fairly increasing relevance in the last decades are: (i) the combination and the comparison of the results obtained by applying different methods, and (ii) the research efforts to define multiple criteria DSSs to tackle the problems identified in prior case studies. *AR5*. Researchers noticeably tend to analyze the problems with fuzzy set theory and linguistic variables after the mid-1990s to handle ambiguity and uncertainty in policy makers' assessments.	*AC1*. Choosing among all the existing methods can be deemed as a multiple criteria decision-making problem. Each method has its strengths and weaknesses, and it is impossible to claim that any specific method generally outperforms the other ones. *AC2*. The choice of a method mostly depends on the preferences of the decision maker and the analyst. Additionally, the suitability, validity and user friendliness of the methods shall be also considered. *AC3*. As a result of the shift towards RES, researchers try to utilize and enhance the available knowledge in decision-making. *AC4*. Validation of results with multiple methods, development of interactive DSSs and application of fuzzy methods to deal with uncertainty in data, are widely observed aspects in the existing literature. *AC5*. Fuzzy set theory, the use of multiple methods in the same application and the development of novel user-friendly methods, are arguably major future trends in the field of energy planning.
R2 Borunda et al. [50]	62	Undefined	*RC1*. A bibliographical survey, covering state-of-the-art applications of Bayesian Networks (BNs) in renewable and sustainable energy, as well as other related areas (e.g. energy assessment). *RC2*. A tabular report summarizing the current state of the research undertaken per relevant each energy source, and forthcoming directions. *RC3*. Related literature to the use of BNs in renewable and sustainable energy is categorized by areas, according to three dimensions: resource evaluation, operation, and applications.	*AR1*. Main applications of BNs include: forecasting, fault diagnosis, maintenance, operation, planning, risk management and measuring. *AR2*. Most applications are focused on wind and hydroelectric energy, whilst biomass, geothermal, solar thermal and photovoltaic energy are the least investigated ones. AR3. Dynamic Bayesian Networks (DBNs), which naturally address the additional complexity of dynamic systems, have been applied in wind energy, energy storage, energy market and energy assessment.	*AC1*. BNs are promising and highly versatile tools for renewable and sustainable energy, with a range of potential applications. BNs can be useful to optimize the technologies involved in the renewable energy market, so as to improve the overall resource usage with an associated cost reduction. *AC2*. BNs can easily encode human knowledge and expertise, historical data or both, helping users to update models and turning the model more correct and trustworthy. *AC3*. BNs support inference in any direction, providing responses to any type of query predicated on a source of evidence and modeling dynamic systems in a straightforward manner. *AC4*. A myriad of opportunities are yet to be explored by using BNs and DBNs in this field, such as: resource forecasting, risk assessment/management, decision support, design/sizing/optimization, planning, and energy sources integration.

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Table 2 *(continued)*

# Reference (Year)	Included articles	Period(s)	Review characteristics	Authors' summary of results	Authors' conclusions
R3 Pérez-Ortiz et al. [51]	55	Undefined	*RC1*. A review of classification problems and applications of related approaches in renewable and sustainable energy domains. *RC2*. The review investigates existing classification algorithms and how these approaches have been applied to deal with diverse types of renewable and sustainable energy. *RC3*. A comprehensive discussion on different classification techniques in specific renewable and sustainable energy problems. *RC4*. A categorization is provided according to the application field, the problem tackled and the specific methodology considered.	*AR1*. Classification and related techniques have proved themselves extremely important in the area of machine learning (ML), with applications in different fields, including renewable energy problems. *AR2*. A large amount of applications and problems involving different aspects of renewable energy systems, can be effectively tackled via classification algorithms. *AR3*. Five major lines of research in RES can be intuitively regarded as classification problems: wind speed/power prediction, fault diagnosis, power disturbance analysis, appliance load monitoring, and renewable and sustainable energy alternative problems. *AR4*. Special attention is devoted to classification methods based n support vector machines (SVM) and artificial neural networks (ANNs), given their ability to handle non-linear and noisy data.	*AC1*. The use of ML (and more specifically, classification techniques) has been crucial for the area of renewable and sustainable energy systems in the last few years, with their impact expected to continue in upcoming years. *vAC2*. Different RE applications can be modeled as classification problems and solved by using ML techniques. *AC3*. Although deep learning research is still at an early stage, the authors believe that its future proliferation will enable the definition of more complex and accurate models with straightforward RE applications. *AC4*. The authors convincingly argue that many challenges arising in the future intelligent electrical network will be also deemed as classification problems, and handled by the algorithms reviewed (or improved versions of them).
R4 Horschig and Thrän [52]	180	2005–2016	*RC1*. A systematic overview on latest policy modeling approaches and their capability to estimate a successful implementation of RES policies. *RC2*. A decision support framework to aid decision makers and scientists selecting an approach for policy evaluation modeling, predicated on the question to be answered. *RC3*. A tabular overview that allows the reader to quickly derive information on the suitability of the several modeling approaches. *RC4*. A classification of existing works that distinguishes between quantitative, qualitative, and hybrid approaches.	*AR1*. There are seven "most commonly applied" modeling approaches in renewable and sustainable energy policy evaluation, namely I/O (input/output) modeling, computable general equilibrium modeling, system dynamics modeling, agent-based modeling, theory-based evaluation, MCA, and hybrid approaches. *AR2*. Quantitative approaches models are more frequently used for the evaluation of renewable and sustainable energy policies. *AR3*. Agent-based modeling is the preferred option to model the relation between agents in markets at a regional scale. *AR4*. I/O modeling is used for the simulation of short-term effects. *AR5*. The required quality of data sources varies from one approach to another.	*AC1*. Each methodology manifest obvious characteristics that make them unsuitable for some specific problem. *AC2*. In contrast to some other approaches, MCA can be implemented in computing frameworks. However, its major drawback is its inability in deriving decision information on whether undertaking an action is better than doing nothing. *AC3*. All modeling approaches have their strengths and weakness, hence none of the modeling approaches can be considered as superior *per se*. Nevertheless, hybrid methods tend strike a more positive balance in an homogeneous context, achieving more robust results and minimizing (or even eliminating) the drawbacks of using a simple approach. *AC4*. The parallel application of different approaches can also provide a better understanding the robustness of results in the different models. Another promising avenue is the development of linkages between already existing models.

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Table 2 *(continued)*

# Reference (Year)	Included articles	Period(s)	Review characteristics	Authors' summary of results	Authors' conclusions
R5 Mardani et al. [53]	196	1995–2015	*RC1*. A review focused on the application of decision-making approaches in relevant energy planning problems. *RC2*. 72 international scholarly journals indexed in Web of Science database. *RC3*. The PRISMA (systematic and meta-analysis) method was used to conduct the review. *RC4*. Data have been extracted and summarized according to: main areas, authors, publication year, technique and application, number of criteria, research purpose, gap and contribution, results and findings, etc.	*AR1*. Hybrid MCDM and FMCDM in the integrated methods were ranked as the most primarily utilized methods in the literature. *AR2*. The Journal of *Renewable and Sustainable Energy Reviews* constituted the most representative source for the study, with 32 published papers reviewed. *AR3*. The area of Environmental impact assessment was ranked as the main target application of decision-making approaches. *AR4*. Decision-making approaches can help decision makers and stakeholders solving some problems under uncertainty situations in environmental decision-making.	*AC1*. Little attention has been paid to the preparation of decision-making matrices, along with an insufficient justification on which, how, and why authors have chosen one specific method for data normalization or another. *AC2*. There is a shortage of research dedicated to the application of decision-making theories and methods under fuzzy aggregation operators in energy development issues. *AC3*. Future papers may focus on integrating MCDM methods with recent extensions of fuzzy set theory, fuzzy integrals and aggregation operators. *AC4*. Future studies may combine MCDM techniques with qualitative information and quantitative data based on fuzzy linguistic term sets and fuzzy ordered weighted operators. *AC5*. Scholars show ongoing interest in interval-valued intuitionistic fuzzy sets, so as to integrate MCDM methods with Interval-valued intuitionistic fuzzy weighted arithmetic, ordered weighted, or hybrid aggregation operators.
R6 Kumar et al. [54]	Undefined (≳140)	Undefined	*RC1*. This survey develops an insight into various MCDM techniques, progress made by considering RES applications over MCDM methods and future prospects in the area. *RC2*. An extensive review illustrates important features of the MCDM problem, various algorithms available and highlights of their various features in the context of RES-based energy planning. *RC3*. A brief summary of popular decision analysis and dedicated software packages related to MCA. *RC4*. The paper surveys methods showing typical steps involved along with their area of application, strengths and weaknesses.	*AR1*. MCDM has emerged as a popular tool with numerous applications in many subject areas. *AR2*. Broadly, three types of MCDM models are distinguished, namely value measurement models, goal, aspiration and reference level models and outranking models. *AR3*. AHP has gained popularity due to its simplicity in procedure. Notwithstanding, the outranking techniques ELECTRE III and PROMETHE are not less popular. These models have been also used in combination. *AR4*. Based on the data obtained from *quacquarelli symonds* world ranking, the authors provide a graphical representation that indicates the number of top 200 universities in the world which adopted the MCDM techniques for interdisciplinary research. *AR5*. The available software packages related to MCA are commercially (or otherwise readily) available. *AR6*. In terms of developing nations, a total of 39 performance indicators (under technical, economical, social, environmental and institutional dimensions) can be used for efficient designing of electrification system.	*AC1*. No single MCDM model can be ranked as best or worst. Every method has its own strengths and weaknesses depending on its EPDM application. *AC2*. Hybrid techniques are thereby being developed to tackle complex situations. *AC3*. MCDM is not only viewed as a method, but also as the means to capture all the consequences and objectives of planning. *AC4*. MCDM is still absent at local organizational level. Most MCDM models are implemented in areas associated with a national, regional or a particular geographical location. Further analysis is required considering local resources for local environment. *AC5*. Sustainable Energy planning should be evaluated not only considering a single scenario based on multiple criteria, but evaluation should be done considering multiple scenarios based on multiple criteria. *AC6*. Achieving the best solution and overcoming environmental/local issues in real-time applications, demands MCDM models under multiple scenarios and criteria.

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Table 2 *(continued)*

# Reference (Year)	Included articles	Period(s)	Review characteristics	Authors' summary of results	Authors' conclusions
					AC7. New *modus operandi* could be formulated to tackle diverse dimensions of energy and environmental planning.
R7 Bhowmik et al. [55]	206	1957–2017	*RC1*. A review on various works conducted under distinct perspectives, e.g. integrated approaches, MCDM methods, etc., for green energy planning and scheduling problem. *RC2*. A classification and analysis of relevant research articles aimed at: (i) finding out the most popular approach adopted in the sustainable energy evaluation and selection and (ii) discovering the most commonly considered criteria by decision makers in assessing and selecting the best green energy sources available globally.	*AR1*. The most famous individual approach is mathematical programming using different algorithms, followed by fuzzy approaches, hybrid energy management of physical systems, ANP, ZigBee technology, AHP, data envelopment analysis (DEA), ANN, genetic algorithm (GA), etc. *AR2*. The unified GA with ANN is reported as more reliable to predict the sustainable future. In addition, GA has been integrated alongside other approaches such as DEA, fuzzy set theory, grey relational analysis, MCDM and multi-objective programming approaches. *AR3*. Most of the articles show that various techniques had been implemented for optimal green energy planning in different regions across the globe.	*AC1*. The traditional single or multiple criteria approach based on minimizing costs is no longer supported and robust enough for RES selection. *AC2*. Managing the RES by using different hybrid optimization tools and MCDM techniques would be significantly helpful for decision makers. *AC3*. It is estimated that the number of works will keep increasing in the coming years because of the importance of sustainable energy planning. *AC4*. In many cases, the weights of criteria are assigned arbitrarily without considering the "right to be heard" of ordinary people. *AC5*. ENTROPY-AHP, ANP,TOPSIS, or COPRAS methods and AHP-ABC analysis have not been applied to RES evaluation and selection problems yet.
R8 Martín-Gamboa et al. [2]	62 39	until March 2016 until June 2016	*RC1*. The first literature review focuses on MCA for sustainability assessment of energy systems (Scopus search). *RC2*. The first review aims to identify - through content analysis - the most commonly used criteria, data sources and MCA tools for sustainability assessment of energy systems. *RC3*. The second literature review has focus on the combined implementation of life-cycle (LC) approaches and DEA models for the sustainability assessment of energy systems. *RC4*. The central objective is to explore and elucidate potentials of the aforementioned hybrid approaches within sustainability-oriented MCDM. *RC5*. The review presents the number of *LC + DEA* studies published according to the year of publication and the countries involved (Scopus search).	*AR1*. The first review shows a significant increase in the number of publications since 2010. *AR2*. The LC + DEA concept has gained increasing popularity in recent years, with a growing international coverage (second review). *AR3*. The most common MCA methods are inspired by the multi-attribute value theory (MAVT) family of methods. Within MAVT, it is common to find AHP and MAUT approaches. Outranking methods are also common MCA options. *AR4*. Four key methods are included in the distance-to-target category: TOPSIS, VIKOR, grey relational analysis, and DEA. *AR5*. The remaining categories analyzed show a lower number of occurrences in existing literature. *AR6*. As an original result of potential issues identified through the review process, a novel methodological framework based on LCA, DEA and energy systems modeling is proposed for enhanced energy planning.	*AC1*. The choice of a specific MCA method is highly dependent on the particular features of each problem and the decision-makers' needs. *AC2*. Within the MCA tools reviewed, particularly within the distance-to-target methods, DEA arises as a trade-off solution between soundness and practicality. *AC3*. The application of DEA as an MCA tool for sustainability assessment is still untapped. The minor role currently played by DEA in sustainability assessment of energy systems should be understood as an opportunity. *AC4*. The LC + DEA concept emerges as a feasible MCDM methodology when data stem from multiple homogeneous entities, thus supporting complex decision-making processes. *AC5*. The use of a novel methodological framework based on LCA, energy systems modeling and DEA is recommended for enhanced energy planning.

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Table 2 *(continued)*

# Reference (Year)	Included articles	Period(s)	Review characteristics	Authors' summary of results	Authors' conclusions
					AC6. The combination of LC approaches and DEA inherits the advantages of both methodologies, while overcoming some of their limitations and producing an easy-to-report and easy-to-interpret results.
R9 Vassoney et al. [56]	45	until October 2015	*RC1*. A review of state-of-the-art MCA applications to sustainable hydropower production and related decision-making problems. *RC2*. A detailed analysis of scientific papers published in the topic over the last 15 years. *RC3*. The papers were analyzed and compared, based on specific features of MCA methods, highlighting the general aspects of the MCA application (purpose, spatial scale, software used, stakeholders, etc.) and the specific operational/technical features of the selected MCA technique (methodology, criteria, evaluation, approach, sensitivity, etc.).	*AR1*. An increasing trend across the time of MCA applications to hydropower use and management problems. *AR2*. A vast majority of papers (86.7%) refers to real case studies in which MCA is undertaken with real data. *AR3*. There are no publications describing whether MCA results were applied to support the decision-making process, not only at a theoretical level, but also leading in practice to economical and political decisions. *AR4*. Several articles lack references to the participation of experts and stakeholders in the decision-making process or, even if the authors declared a participatory approach, the subjects actually involved in the case study are not specified. *AR5*. The most applied MCA technique turns out to be AHP, which is occasionally used in conjunction with other methodologies or extended into a fuzzy context. *AR6*. Sensitivity analysis was applied to investigate the consistency of results, usually by modifying the weights of some indicators to observing the possible effects on preferences over alternatives.	*AC1*. The lack of several significant information in numerous papers (e.g., actors involved, the use of MCA results in the real case study, etc.) prevent a general understanding on how MCA supported the decision-making process or whether the MCA results were (at least) taken into account by stakeholders. *AC2*. A bottom-up approach is generally difficult to undertake (e.g., the choice of criteria and indicators is usually made by the authors of the paper, usually based on a literature review or expert consultation). This may be due to the difficulty to promote the participation of different stakeholders, taking into account their concerns and interests and facing the divergence of their perspectives, point of view and values. *AC3*. Future MCA applications should adopt a more participatory attitude at all levels of the modeling procedure whilst ensuring that all stakeholders and experts involved in the process are able to participate and contribute actively to the modeling process.

Table 3
Electronic databases investigated in this review.

#	Electronic databases
EDB1	ScienceDirect
EDB2	ISI Web of Science
EDB3	IEEE Xplore
EDB4	ACM Digital library
EDB5	SpringerLink
EDB6	Wiley InterScience
EDB7	Google Scholar

Table 4
Target domain journals investigated in this review.

#	Domain journal
	(Renewable) energy
EJ1	Renewable and Sustainable Energy Reviews
EJ2	Journal of Cleaner Production
EJ3	Energy
EJ4	Energy Conversion and Management
EJ5	Energy Policy
EJ6	Applied Energy
EJ7	Renewable Energy
EJ8	Environmental Science & Technology
EJ9	Energy & Fuels
	Computer science
CSJ1	MIS Quarterly
CSJ2	Information Sciences
CSJ3	Decision Support Systems
CSJ4	Knowledge-Based Systems
CSJ5	Future Generation Computer Systems
CSJ6	Expert Systems with Applications
CSJ7	European Journal of Operational Research
CSJ8	Computers & Operations Research

FMCDM approaches. Their study reviewed a total of 403 papers published from 1994 to 2014 in more than 150 peer-reviewed journals. Selected papers were grouped into four main fields: engineering, management and business, science, and technology. Furthermore, these papers were categorized based on authors, publication date, country of origin, methods, tools, and type of research. Interesting results of this study indicated that FMCDM and fuzzy AHP were ranked as the first and second methods in terms of usage; and engineering domain was ranked as the most applied field by fuzzy decision-making models.

Suganthi et al. [39] focused their review on the applications of fuzzy logic based models in renewable and sustainable energy systems. They argue that fuzzy based models have been extensively used in recent years for different EPDM planning situations (e.g., site assessment, photovoltaic/wind farms installation, power point tracking in solar photovoltaic/wind, etc.). In addition, the authors pointed out the widespread use of fuzzy AHP and fuzzy ANP methods in identifying the relative importance of RES-related alternatives, schemes, and project plans. They conclude that researchers can adopt fuzzy based modeling to provide pragmatic solutions in solving the energy-environment problems.

Antunes and Henriques [6] proposed one of the most complete and exhaustive reviews of MOO and MCA models and methods for different problems in the energy sector. Their review analyses models and methods dealing with optimization and decision-making concerns in a vast range of energy problems, throughout a selection of papers appearing in international journals in the 21st century, mostly in the areas of operational research and energy. The authors investigated the structure of models and methods to tackle the most frequent types of problems reported in the literature. The main conclusion is that MOO and MCA models and methods gained an increasing importance in the appraisal of energy technologies and policies across a vast range of energy planning problems, decision levels and timeframes, in order to generate usable recommendations that balance multiple, conflicting, and incommensurate evaluation aspects. Additionally, the authors expect that the energy sector will remain one of the most active and exciting areas of application of MOO/MCDM models and methods, with an enriching cross-fertilization between challenging problems and innovative methodologies to tackle them.

The above-discussed works are highly-cited reviews over the last 15 years that attempted– under different perspectives –to investigate problems concerning systems, methods, models, and techniques in EPDM. In addition to these efforts, Table 2 presents a summary of nine [1,2,50–55] of most recent attempts to overview latest EPDM solutions. The tabular overview covers similar aspects as those discussed in previous reviews, along with the total number of included articles, the covered period(s) of the publications, the main characteristics of the review, the authors' summary of results, and most importantly the authors' final conclusions. Our purpose is to provide the interested reader with concise, yet comprehensive and meaningful information about these recent EPDM literature reviews. Several more recent literature reviews [3,8,122,141,153,161,162] have been left out of the scope of this paper, since their main focus was on management aspects exclusively.

Most previous efforts in reviewing state-of-the-art research EPDM tried to investigate only specific energy planning concerns (e.g., the assessment of RES investments [1], classification problems in RES [51], renewable and sustainable energy policy modeling [52], sustainability assessment of energy systems [2], etc.) while targeting only a particular EPDM solution (e.g., bayesian networks [50], MOO [2,5,6], MCA [6,10,57], fuzzy and FMCDM approaches [60], etc.). In other words, none of these works cover all EPDM challenges and their related solutions. Furthermore, most reviews apply classical classification strategies to categorize the results predicated on publication date, application areas, authors nationalities, used methods, type of research, etc., and concentrate on communicating the trends, methods and application areas by using bibliometric/meta-analysis, and distributions of the selected articles over different attributes [1,53–55].

To the best of our knowledge, none of the existing literature reviews attempted to summarize the different processes or decision support tools in a structured framework to aid decision makers in recognizing for instance, the different stages of exploiting/promoting the available RES that require more attention. Specifically, from a computer science design point of view, there is a shortage of clear classifications and studies of existing literature regarding the strategic operations of RES. Computer science contributions are still unclear in these operations, and innovative aspects are undefined due to rapid changes in the renewable and sustainable energy field. Additionally, most of the existing literature reviews try to answer classical research questions such as: Which approaches were predominantly applied in a particular EPDM situation? How these approaches have been applied to EPDM situations? What are the advantages and drawbacks of the approaches? Which evaluating criteria were paid more intentness to energy plan-

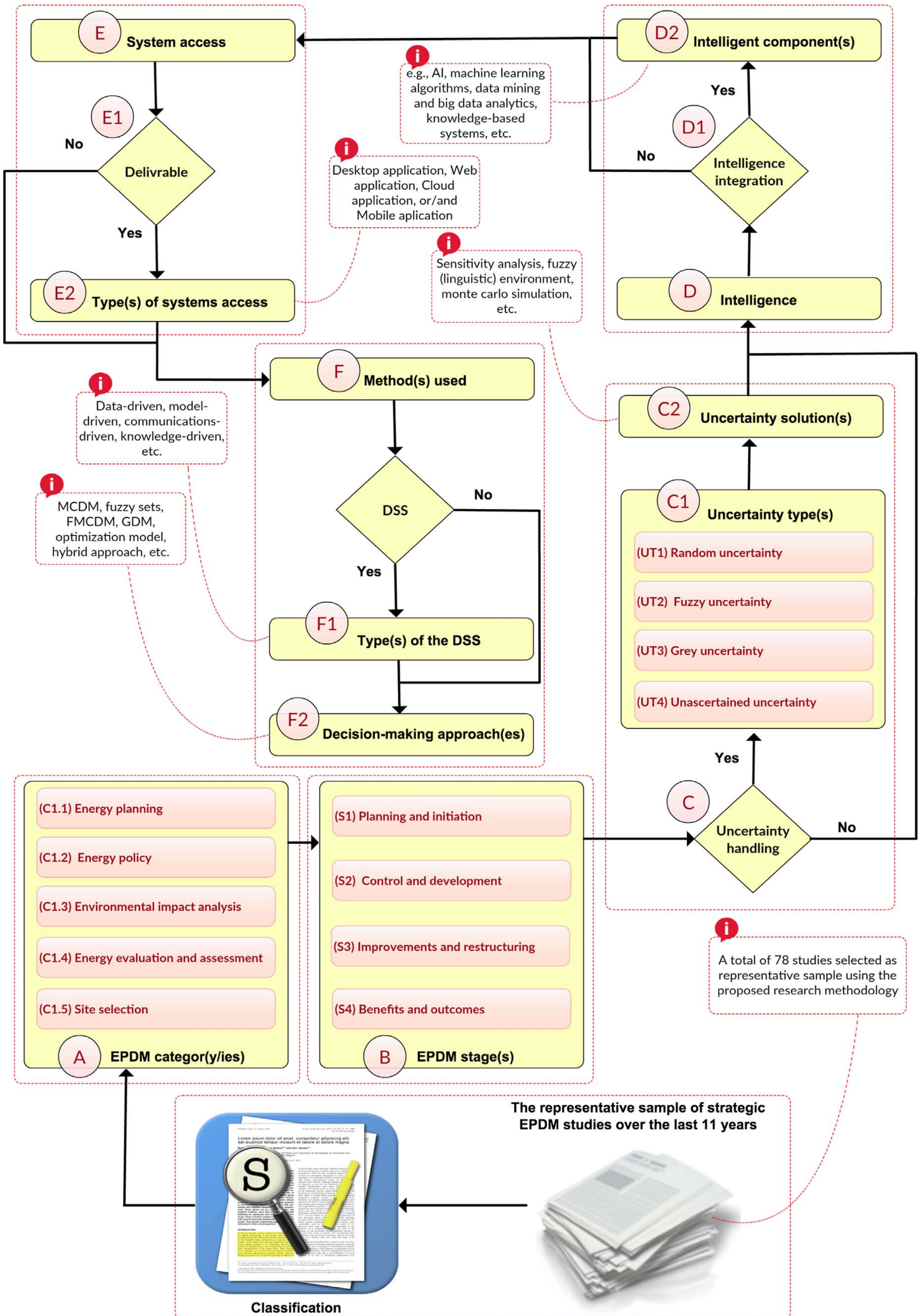

Fig. 1. Classification of strategic EPDM studies.

ning for sustainable development? [2,55]. Moreover, to our knowledge, none of the previous reviews tried to investigate in a systematic way all problematics, limitations, and complexities in EPDM solving solutions.

Therefore, we consider the limitations highlighted above in order to outline the current complexities, trends, and potential future research lines of enquiry on this research topic. The next subsections describe the research methodology and the proposed detailed classification of the selected papers. Importantly, we note that the results and conclusions drawn from existing literature reviews in this section must be interpreted as support and complementary evidence to the statements of this paper.

2.2. Research methodology

The primary purpose regarding the ongoing literature review is to investigate the complexities and challenges of EPDM solutions, so as to identify directions of work towards improved and more effective decision-making solutions in the future. Relevant studies are retrieved automatically, by querying multiple electronic databases (see Table 3), as well as manually, from target indexed, in *Scopus* and *Web of Science* database peer-reviewed domain– (renewable) energy and computer science –journals (see Table 4). The study selection process in both databases, and target journals consists of three successive phases.

Initially, a search strategy is first applied in order to identify potential studies. A set of search terms is proposed and various combinations using boolean operators ("OR" and "AND") are used to join them: energy planning OR renewable energy OR <X>) AND (decision support system OR DSS) AND (MCDM OR multiple criteria decision-making OR multi-criteria decision-making) AND (fuzzy OR fuzzy theory OR fuzzy set OR fuzzy logic) AND (uncertainty OR artificial intelligence OR AI OR knowledge-based OR web-based), etc. Importantly, the string <X> was replaced with each of the individual RES names (e.g., solar power, PV, geothermal, hydro power, biomass, etc.).

Next, formal searches are performed in two sub-steps sequentially: (i) the automatic search in the selected databases and (ii) manual search in the target domain journals. Additionally, this paper's authors decided to use the snowballing[1] approach only on citations that highly matches the target investigations by this review [163,164], as an additional and effective way to search for relevant literature.

Then, in each phase, titles, abstracts, and full-texts of potential studies have been analyzed against some pre-defined criteria in order to decide whether each paper should be included or not. Non-English studies, studies not covering decision-making in energy planning issues belonging to the categories within the strategic decision level (see DL.1. in Table 1), and studies with an application of DSSs not belonging to at least one of the categories between parenthesis (energy, knowledge-based and expert systems, uncertainty and AI techniques, web-based applications), were not taken into account in this literature review. More generally, we identified representative studies that proposed theoretical or/and practical solution(s) to strategic EPDM applications such as: comparison of power generation technologies, evaluation of energy plans and policies, selection of energy projects, and siting decisions. Disagreements about paper selection in unclear/boundary cases have been managed throughout discussion between all the participants in this review.

As previously stated, the present study is aimed at extracting a number of relevant insights and remarks from the strategic EPDM literature that enables us to build a clear understanding of its limitations, trends, and potential future research lines. A notable challenge was to maintain a manageable amount of selected works whilst still objectively and comprehensively representing the current state-of-the-art of the investigated topic: more than 300 papers remained when applying the first phase of the search procedure. The second step was to identify additional criteria in order to reduce the number and to have a basis for the construction of a classification strategy. Therefore, studies from 2005 and onwards are considered with the focus on most cited, relevant, and recent case studies regarding renewable and sustainable energy planning. More precisely, studies that implemented a DSS for one or more strategic EPDM categories are prioritized. Applying the additional criteria, a total of 78 studies are chosen as the representative sample.

In the sequel, we shall first refer to the classification used to categorize the most frequently used decision support tools applied to strategic EPDM problems. Then, the representative sample of articles is presented and categorized based on the proposed classification.

2.3. Classification

Within the analysis of the selected articles, several patterns were observed. In this sense, to classify relevant works (strategic EPDM solutions), we use the following parameters to investigate their strengths, weaknesses, and more importantly their suitability to handle different aspects in strategic EPDM: (A) the *EPDM categor(y/ies)* from Table 1, (B) *EPDM stage(s)*, (C) *Uncertainty handling* feature, (D) *Intelligence* integration, (E) available *System access* and user-friendly interfaces, and last (F) the decision-making *Method(s) used* as problem-solving. In parallel, we focus on the identification of strategic EPDM categories and stages of exploiting and promoting the RES that demand future considerations from researchers and computer scientists alike. Then, the rest of the classification parameters– (C), (D), (E), and (F) –are considered to facilitate targeting the major interest of this study– complexities and challenges of EPDM solutions –whilst allowing a differentiation from previous literature reviews. Fig. 1 depicts the overall process of the classification, whose main parameters, except (A) (see Table 1), are developed in the following subsections.

2.3.1. EPDM stages

We consider a scenario that covers the fundamental stages to initiate an energy planning project, distinctly, the ones that tend to exploit and develop the available RES for a better and sustainable world. The description of the considered scenario's stages and associated decision-making examples are given in Table 5. This scenario involves four successive *EPDM stages* from (S1) the *Planning and initiation* of a renewable and sustainable energy project, (S2) project's *Control and development*, (S3) *Improvements and restructuring*, to (S4) project's evaluation to measure actual and future *Benefits and outcomes*. Whilst doing so, existing decision support tools and methods for restructuring the energy sector, concerning patterns of energy extraction, generation, transformation and use, from unsustainable to sustainable forms of development are identified for each of the above-defined stages. In other words, the objective is to classify the different selected papers in a structured way to aid policy and decision makers in recognizing the different *EPDM stages* and their existing related tools. Additionally, this resolution will help to point out stages that might need to be further investigated which give researchers and computer scientists alike insights on existing issues and potential improvements.

[1] Snowballing refers to the continuous, recursive process of gathering, searching, scanning and using the reference list of a paper or the citations to the paper to identify additional papers.

Table 5
The proposed EPDM stages.

#	Stage	Description	Decision (s)
S1	Planning and initiation	This stage refers to exploiting available RES to develop different projects that will make people's life better in every way possible (e.g., power generation plants, smart grids, homes, and buildings, energy-saving systems, green and sustainable industrial development, etc.)	Selection of energy projects, investments and projects' portfolio optimization, cost benefit analysis, risk analysis, siting decisions, evaluation and selection of energy plans and policies, etc.
S2	Control and development	One of the keys to project success is the monitoring. Projects in first stages of development need special control of all available resources to insure their continuity and optimization.	Resources availability and optimization, operational level monitoring, evaluation of energy efficiency measures, human resources management, etc.
S3	Improvements and restructuring	Each project will unquestionably encounter various types of problems. The decision makers need to consider practical corrective actions and figure out effective solutions in order to restructure or improve their project.	Crisis management, intelligent support, knowledge use and sharing, etc.
S4	Benefits and outcomes	The aim of developing every project is to achieve remarkable benefits. These benefits are mainly financial (project holders' gains), social (jobs creation), and environmental (the sustainability worldwide concern).	Energy use and consumption, consumer satisfaction, environmental impacts assessment, project assessment, reporting, etc.

2.3.2. Uncertainty handling

As explained by Mirakyan and Guio [165]: “in the last decades and in a competitive energy market, the need for uncertainty analysis becomes important for different reasons.” EPDM involves many sources of uncertainty due to internal and external factors. Mostly, these sources are the result of inconsistency or imprecision in data and the subjectivity or vagueness of human (decision makers) judgments. Additionally, most of the input data and parameters required by the decision-making methods cannot be given precisely [6]. For instance, in an MCDM context providing exact numerical values for the criteria (precise evaluations) is often beyond decision maker reasoning and capabilities. Several taxonomies and concepts of uncertainty have been proposed in recent years (e.g., linguistic uncertainty, knowledge/epistemic uncertainty, variability/aleatoric uncertainty, decision uncertainty, procedural uncertainty, etc.). Gu et al. [166] identified four interrelated categories of uncertain information:

UT1. *Random uncertainty* which is due to inadequate conditions or the interference from causal factors;
UT2. *Fuzzy uncertainty* which is caused by fuzzy extension of unknown information;
UT3. *Grey uncertainty* which means part information is known but other is unclear, missing or unavailable;
UT4. *Unascertained uncertainty* referring to that decision makers cannot fully grasp the true state, nature of things, or quantitative relations which causes a subjective uncertainty.

Each type of these uncertainties has been addressed by different approaches such as: sensitivity analysis [14,97], scenario based analysis [88], fuzzy sets [34,42,167], etc. Therefore, the sensitive and complex nature of EPDM require processing all the different types and sources of uncertainty to provide decisions in which the decision maker can have confidence [6]. However, even if many sources of uncertainty are recognized, there is still a lack of agreement on a unified typology, characteristics, relative magnitudes, and available approaches for dealing with them [84].

The aim of this study is to demonstrate how the importance and benefits of dealing with uncertainty have evolved across the time in the strategic EPDM related literature. Accordingly, integrating the active parameter (*Uncertainty handling*) in our proposed classification indicates if a selected paper tried to propose an approach to handle one or more specific type of uncertainty or not. Thus, the *Uncertainty type(s)* (C1) is firstly identified according to the above-mentioned four categories [166]. Then, the proposed *Uncertainty solution(s)* (C2) to deal with each type of uncertainty is identified. The aim is to investigate uncertainty handling and treatment in strategic EPDM context whereas an extensive literature review of uncertainty in EPDM will be further investigated in a future work.

2.3.3. Intelligence

Decision-making for renewable and sustainable energy promotion and development requires intelligent solutions that enable managing growing complexities of strategic energy planning and specific management operations. The EPDM literature contains numerous references to intelligent tools that have been specifically designed to different management operations (energy resources management [32], energy-saving [142,144], smart grid management [154], intelligent building [168], demand side management [136], energy demand [130], and so on). On the other hand, none of the previous literature reviews–referenced in this paper –investigated the use of AI techniques, ML algorithms, or the integration of other effective intelligent components in strategic energy planning. The numerous ecological, socio-economical, and political constraints EPDM processes involved, along with the presence of interrelated perspectives, conflicting objectives, and (a large number of) involved stakeholders with different aims and preferences [15,16] further complicate the decision-making problem. In such situations, the planners (or decision makers) often are not fully aware of (i) the range of factors involved, (ii) the implications of the other participants, and more importantly (iii) hidden aspects that require deeper investigations and might completely change and affect the final decisions [169,170]. It is sometimes not until after generating a proposed action that unforeseen consequences become perceptible or evident and that a reconsideration of the whole decision-making process that generated this decision becomes necessary [49]. The most

Table 6
A summary of the strategic EPDM solutions proposed over the last 12 years.

Author(s) (Year)	EPDM category	Uncertainty type(s)	Intelligence integration	System access	Method(s) used
	EPDM stage(s)	Uncertainty solution(s)	Intelligent component(s)		
Ramachandra et al. [18]	C.1.4	×	×	Desktop application	data-driven and spatial DSS; GIS; reporting; simulation
	S1	×	×		
Ramachandra et al. [184]	C.1.4 & C.1.5	×	×	Desktop application	data-driven DSS; EIS; GIS; reporting; simulation
	S1	×	×		
Chui et al. [185]	C1.3 & C.1.4	×	×	×	MCDM; AHP; LCA; hybrid approach
	S1 & S3	×	×		
Yue and Yang [19]	C.1.1 & C.1.4	UT3	×	×	model-driven DSS; GIS; cost analysis
	S1 & S4	sensitivity analysis	×		
Patlitzianas et al. [20]	C.1.2 & C.1.4	×	×	Desktop application	knowledge and model-driven DSS; ES; MCDM; knowledge base
	S1 & S3	×	×		
Frombo et al. [21]	C1.4 & C1.5	×	×	Desktop application	model-driven and environmental DSS; GIS; optimization model
	S1 & S3	×	×		
Cai et al. [22]	C1.2, C1.3 & C1.5	UT4	×	Desktop application	model-driven and interactive DSS; optimization model
	S1 & S3	interval linear programming	×		
Kahraman et al. [186]	C1.4	UT2 & UT4	×	×	FMCDM; axiomatic design; fuzzy AHP; hybrid approach
	S1 & S3	fuzzy linguistic environment	×		
Simão et al. [49]	C1.1 & C1.5	×	√	Web application	model and communications-driven, Web-based, and spatial DSS; MCDM; GIS; argumentation map
	S1 & S3	×	learning environment		
Lin et al. [23]	C1.1, C1.2 & C1.3	×	×	Desktop application	model-driven DSS; optimization model
	S1, S2 & S3	×	×		

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Table 6 *(continued)*

Author(s) (Year)	EPDM category	Uncertainty type(s)	Intelligence integration	System access	Method(s) used
	EPDM stage(s)	Uncertainty solution(s)	Intelligent component(s)		
Doukas et al. [93]	C1.4	UT2	×	Desktop application	model-driven DSS; linguistic TOPSIS, 2-tuple fuzzy linguistic representation model
	S1 & S3	fuzzy linguistic environment	×		
Kaya and Kahraman [34]	C1.4 & C1.5	UT2	×	×	FMCDM; integrated VIKOR-AHP; hybrid approach
	S1	fuzzy linguistic environment	×		
Cinar and Kayakutlu [104]	C1.2 & C1.4	UT1	√	×	scenario-based decision-making; forecasting
	S1 & S3	scenario based analysis	causal maps & BNs models		
Kaya and Kahraman [42]	C1.4	UT2	×	×	FMCDM; fuzzy TOPSIS; hybrid approach
	S1 & S3	fuzzy linguistic environment	×		
Dagdougui et al. [24]	C1.1 & C1.5	×	√	×	model-driven DSS; MCDM; GIS; statistical analysis
	S1 & S3	×	ANN		
El-Gayar et al. [180]	C1.1, C1.4 & C1.5	×	×	Web Application	data and model-driven, Web-based and environmental DSS; GIS; Web service; analysis tool
	S1 & S2	×	×		
Cristóbal [106]	C1.4	×	×	×	MCDM; VIKOR; AHP; hybrid approach
	S1	×	×		
Jetter and Schweinfort [187]	C1.1 & C1.4	UT1 & UT2	×	×	scenario-based decision-making; fuzzy cognitive maps
	S1 & S3	fuzzy environment	×		
Choudhary and Shankar [14]	C1.5	UT2	×	×	FMCDM; fuzzy AHP; TOPSIS; fuzzy linguistic environment; hybrid approach
	S1 & S3	sensitivity analysis	×		

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Table 6 *(continued)*

Author(s) (Year)	EPDM category	Uncertainty type(s)	Intelligence integration	System access	Method(s) used
	EPDM stage(s)	Uncertainty solution(s)	Intelligent component(s)		
Boran et al. [43]	C1.2	UT2	×	×	FMCDM; axiomatic design; hybrid approach
	S1 & S3	fuzzy linguistic environment	×		
Ouammi et al. [26]	C1.3, C1.4 & C1.5	×	×	×	model-driven and environmental DSS; GIS; statistical analysis; mathematical model
	S1 & S3	×	×		
Šliogeriene et al. [28]	C1.4	×	×	Web Application	model-driven and Web-basd DSS; MCDM; multiple criteria complex analysis; recommender model
	S1, S2 & S3	×	×		
Quijano et al. [188]	C1.1 & C1.4	×	×	×	MCDM; GIS; MOO; VIKOR; scenario simulation; hybrid approach
	S1, S2 & S3	×	×		
Daim et al. [189]	C1.1 & C1.4	×	√	×	MCDM; causal maps
	S1 & S3	×	BNs		
Klein [190]	C1.4	×	×	×	MCDM; scenario-based decision-making
	S1 & S3	×	×		
Stein [97]	C1.4	UT4	×	×	MCDM; AHP
	S1 & S3	sensitivity analysis	×		
Akay et al. [88]	C1.4	UT3 & UT4	×	×	MCDM; grey relational analysis
	S1	scenario based analysis	×		
Öztayşi et al. [15]	C1.4	UT2	×	×	FMCDM; fuzzy ANP; BO/CR method; hybrid approach
	S1 & S3	fuzzy environment	×		
Cristóbal [114]	C1.5	UT4	×	×	MCDM; MAUT; utility theory; hybrid approach
	S1	cloud theory	×		
Aydin et al. [191]	C1.5	UT2	×	×	FMCDM; GIS; ordered weighted averaging algorithm
	S1	fuzzy environment	×		

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Table 6 *(continued)*

Author(s) (Year)	EPDM category	Uncertainty type(s)	Intelligence integration	System access	Method(s) used
	EPDM stage(s)	Uncertainty solution(s)	Intelligent component(s)		
Mayer et al. [192]	C1.2 & C1.3	×	×	Desktop application	communications and model-driven DSS; portfolio analysis; informed decisions
	S3	×	×		
Doukas et al. [85]	C1.2 & C1.4	UT2	×	×	MCDM; 2-tuple TOPSIS; hybrid approach
	S2 & S3	fuzzy linguistic environment	×		
Kyriakarakos et al. [30]	C1.1 & C1.4	UT2	×	Web Application	model-driven and Web-based DSS; fuzzy cognitive maps
	S1 & S3	fuzzy environment	×		
Mattiussi et al. [31]	C1.3 & C1.4	×	×	×	model-driven DSS; MCDM, MOO; AHP; LCA
	S1 & S3	×	×		
Troldborg et al. [94]	C1.1 & C1.4	UT4	×	×	MCDM; PROMETHEE
	S1 & S3	monte carlo simulation	×		
Vafaeipour et al. [61]	C1.5	×	×	×	MCDM; GIS; hybrid approach
	S1	×	×		
Tang et al. [193]	C1.4	×	×	×	MCDM; delphi-AHP; hybrid approach
	S1 & S3	×	×		
Öztayşi and Kahraman [167]	C1.4	UT2 & UT4	×	×	FMCDM; interval type-2 fuzzy AHP; hesitant fuzzy TOPSIS; hybrid approach
	S1 & S3	fuzzy linguistic environment	×		
Bessette et al. [194]	C1.1	×	×	×	hybrid decision-support framework; portfolio analysis
	S1 & S3	×	×		
Sharma et al. [40]	C1.4	UT2	×	×	FMCDM; cross entropy method; interval-VIKOR; TOPSIS; hybrid approach
	S1 & S3	fuzzy linguistic environment	×		

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Table 6 *(continued)*

Author(s) (Year)	EPDM category EPDM stage(s)	Uncertainty type(s) Uncertainty solution(s)	Intelligence integration Intelligent component(s)	System access	Method(s) used
Tahri et al. [195]	C1.5 S1	× ×	× ×	×	MCDM; AHP; GIS
Khandekar et al. [41]	C1.5 S1	UT2 fuzzy environment	× ×	×	FMCDM; fuzzy axiomatic design; trapezoidal fuzzy numbers
Guo and Zhao [45]	C1.5 S1	UT2 sensitivity analysis	× ×	×	FMCDM; fuzzy TOPSIS; hybrid approach
Cobuloglu and Büyüktahtakın [196]	C1.4 S1 & S3	UT4 stochastic & sensitivity analysis	× ×	×	MCDM; stochastic AHP
Long and Geng [197]	C1.4 S1 & S3	UT2, UT3 & UT4 fuzzy environment	× ×	×	FMCDM; interval-valued intuitionistic fuzzy set; TOPSIS; entropy weight method; hybrid approach
Montajabiha [198]	C1.1 & C1.4 S1 & S3	UT2 & UT4 fuzzy linguistic environment	× ×	×	GDM; FMCDM; PROMETHEE II; intuitionistic fuzzy set; hybrid approach
Zografidou et al. [67]	C1.2 & C1.5 S1 & S3	UT4 objective criteria	× ×	×	MCDM; optimization model; 0-1 weighted multiperiod goal programming model; DEA; hybrid approach
Nie et al. [199]	C1.1, C1.3 & C1.4 S1 & S2	UT2 fuzzy environment	× ×	×	optimization model; interval type-2 fuzzy fractional programming
Singh et al. [177]	C1.4 S1 & S3	UT2 fuzzy linguistic environment	× ×	×	GDM; FMCDM; interval-valued 2-tuple linguistic variables; PROMETHEE II; entropy method; hybrid approach
Maté et al. [181]	C1.1 S2 & S3	UT3 & UT4 datamining	√ big data	×	forecasting models

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Table 6 *(continued)*

Author(s) (Year)	EPDM category	Uncertainty type(s)	Intelligence integration	System access	Method(s) used
	EPDM stage(s)	**Uncertainty solution(s)**	**Intelligent component(s)**		
Sánchez-Lozano et al. [200]	C1.5	×	×	×	MCDM; AHP; TOPSIS; ELECTRE; GIS; hybrid approach
	S1	×	×		
Sánchez-Lozano et al. [46]	C1.5	UT2 & UT4	×	×	FMCDM; fuzzy AHP; fuzzy TOPSIS; GIS; hybrid approach
	S1	fuzzy environment & sensitivity analysis	×		
Afsordegan et al. [201]	C1.4	UT2	×	×	GDM; FMCDM, qualitative-TOPSIS; fuzzy AHP; hybrid approach
	S1 & S3	fuzzy linguistic environment	×		
Shmelev and van den Bergh [79]	C1.4	UT4	×	×	MCDM; aggregated preference indices system
	S1 & S3	monte carlo simulation	×		
Cebi et al. [110]	C1.5	UT2 & UT4	×	×	FMCDM, AHP, opinion aggregation method, information axiom; hybrid approach
	S1 & S3	fuzzy linguistic environment & sensitivity analysis	×		
Çoban and Onar [202]	C1.1 & C1.4	UT1 & UT2	×	×	scenario-based decision-making; fuzzy cognitive maps
	S1 & S3	fuzzy linguistic environment	×		
Wu et al. [111]	C1.5	UT2, UT3, & UT4	×	×	GDM; FMCDM; ELECTRE-III; generalized intuitionistic fuzzy ordered weighted geometric interaction averaging operator; hybrid approach
	S1 & S3	fuzzy environment	×		
Khishtandar et al. [105]	C1.4	UT2, UT3, & UT4	×	×	FMCDM; hesitant fuzzy linguistic term sets; hybrid approach
	S1 & S3	fuzzy linguistic environment	×		
Ghosh et al. [203]	C1.5	UT2 & UT4	√	×	MCDM; AHP; scenario-based decision-making
	S1 & S3	sensitivity analysis	ANN		
Abaei et al. [109]	C1.5	UT3 & UT4	√	×	MCDM; stochastic models; influence diagram; expected utility
	S1	BN	influence diagram		

(continued on next page)

Table 6 *(continued)*

Author(s) (Year)	EPDM category	Uncertainty type(s)	Intelligence integration	System access	Method(s) used
	EPDM stage(s)	Uncertainty solution(s)	Intelligent component(s)		
Boran [47]	C1.4	UT2 & UT4	×	×	FMCDM; fuzzy TOPSIS; hybrid approach
	S1 & S3	fuzzy linguistic environment	×		
Büyüközkan and Güleryüz [204]	C1.4	UT2 & UT4	×	×	GDM; FMCDM; DEMATEL; ANP; TOPSIS; hybrid approach
	S1 & S3	fuzzy linguistic environment	×		
Baležentis and Streimikiene [205]	C1.1 & C1.2	UT4	×	×	MCDM; integrated assessment models; TOPSIS
	S1	monte carlo simulation	×		
Büyüközkan and Karabulut [206]	C1.4	×	×	×	GDM; MCDM; AHP; VIKOR; hybrid approach
	S1, S3 & S4	×	×		
Jano-Ito and Crawford-Brown [207]	C1.4	×	×	×	MCDM; MAUT; mean-variance portfolio theory; hybrid approach
	S1 & S3	×	×		
Rodríguez et al. [208]	C1.5	UT2 & UT4	×	×	FMCDM; fuzzy AHP; binary index overlay; GIS; hybrid approach
	S1 & S3	fuzzy environment & factor screening method	×		
Strantzali et al. [209]	C1.1 & C1.2	UT4	×	×	MCDM; PROMETHEE II
	S1, S2 & S3	sensitivity analysis	×		
Kim et al. [210]	C1.2 & C1.4	UT4	×	×	scenario-based decision-making; adaptive investment model
	S1, S2 & S3	real options valuation	×		
Chen et al. [211]	C1.4	UT2	×	×	FMCDM; fuzzy ANP; benefits, opportunities, costs and risks concept; hybrid approach
	S1 & S3	fuzzy environment	×		
Papapostolou et al. [212]	C1.2	UT2 & UT4	×	×	GDM; FMCDM; fuzzy TOPSIS; hybrid approach
	S1 & S3	fuzzy linguistic environment & sensitivity analysis	×		

(continued on next page)

Table 6 *(continued)*

Author(s) (Year)	EPDM category	Uncertainty type(s)	Intelligence integration	System access	Method(s) used
	EPDM stage(s)	**Uncertainty solution(s)**	**Intelligent component(s)**		
Chen et al. [183]	C1.1	UT1	×	×	optimization model; two-stage stochastic programming
	S1 & S3	risk-aversion optimization model	×		
Gigović et al. [213]	C1.5	UT4	×	×	MCDM; DEMATEL; ANP; MABAC; GIS; hybrid approach
	S1	sensitivity analysis	×		
Chen et al. [182]	C1.1	UT1 & UT2	×	×	optimization model; copula-based fuzzy chance-constrained programming
	S1 & S3	fuzzy environment	×		
Greco et al. [214]	C1.1 & C1.2	UT1	√	×	investments decision-making; collaboration
	S1 & S3	fuzzy cognitive map	open innovation paradigm		
Gitinavard et al. [215]	C1.1 & C1.4	UT2, UT3 & UT4	×	×	GDM; FMDCM; interval-valued hesitant fuzzy sets; extended maximizing deviation method; DEMATEL; hybrid approach
	S1 & S3	fuzzy linguistic environment & sensitivity analysis	×		
Wu et al. [117]	C1.5	UT2, UT3 & UT4	×	×	MCDM; cloud-based decision-making; pure cloud weighted arithmetic averaging operator
	S1	linguistic environment & sensitive analysis	×		
Mousavi et al. [81]	C1.4	UT2, UT3 & UT4	√	×	GDM; FMCDM; modified approaches; hesitant fuzzy sets; ELECTRE; preferences selection index; hybrid approach
	S1 & S3	fuzzy linguistic environment	experts' weights		
Mosannenzadeh et al. [170]	C1.1	×	√	×	knowledge-driven DSS; normalized hamming distance; radius K-nearest neighbor
	S1 & S2	×	learning methodology		

Table 7
Comparative analysis of classical/traditional and next-generation strategic EPDM solutions.

	Classical/traditional EPDM solution	Next-generation EPDM solution
EPDM categories	At least 1/5 category (usually C1.4) at most 2/5 categories (usually C1.4 & C1.5)	Possibility of solving problems related to 5/5 categories in the same solution
EPDM stages	At least 1/4 stage (usually S1) at most 2/4 stages (usually S1 & S3)	Possibility of solving problems related to 4/4 stages in the same solution
Uncertainty types	At least 1/4 type of uncertainty (usually UT2) at most 3/4 types of uncertainty (usually UT2, UT3, & UT4) simultaneously	Possibility of handling 4/4 types of uncertainty simultaneously
Uncertainty solutions	Classical solutions such as fuzzy (linguistic) environments, sensitivity analysis, monte carlo simulation, and grey analysis	The exploration of new fuzzy sets, assistance from domain experts (i.e., in the form of knowledge bases) during the whole decision-making process, and combinations of different classical uncertainty solutions
Intelligence integration	Absent or partially integrated (few attempts)	Obligatory
Intelligent components	Old-fashioned AI techniques (e.g., ANN), classical learning environments, BNs, forecasting and scenarios analysis	Advanced AI (e.g., deep learning) algorithms, innovative data mining techniques, intelligent knowledge management and ESs
System access	Unavailable and at best a Desktop or Web application	At least 2/4 system access (preferably a Web/cloud-enabled within a mobile application)
Method(s) used	Standalone decision-making method/model	An intelligent, interactive, and extensible DSS
	At best a hybrid approach (combination of MCDM or FMCDM) or a model-driven DSS	A complete hybrid (data, model, knowledge, and communications-driven) DSS
	At least a single decision maker model at best a classical GDM model (i.e., aggregation of decision makers' preferences)	An intelligent GDM model (i.e., intelligent CRP)

frequently used classical decision support methods applied to renewable and sustainable energy problems are conceptually far away from overcoming such complex and perplexing EPDM situations. From this point of view, advanced AI techniques, machine and deep learning algorithms, data mining and big data analytics, and innovative knowledge-based systems are distinguished to be the next considerations of researchers in EPDM. Thus, the active classification parameter (*Intelligence*) is proposed to describe the level of such commitments *Intelligence integration* (D1) from computer scientists in the area of strategic energy planning towards fully exploiting and promoting the available RES. Moreover, this is processed throughout indicating if a proposed study integrates– the combination of – *Intelligent component(s)* (D2) in the decision-making process or not. We also outline a distinction between classical/traditional and (intelligent) next-generation EPDM solutions as another contribution of this study (see Table 7).

2.3.4. System access

The significance of investments and sustainability interests, namely concerning RES, have been relevant factors when EPDM problems have been considered as serious challenges of this century. Thus, the right tools need to be offered to planners and decision makers (governments, investors, regulators, consumers, interest groups, etc.) in order to (i) perform detailed analysis, (ii) obtain balanced recommendations, and (iii) get computerized support in dynamic and complex EPDM environments [6]. Moreover, the sophistication and widespread use of electronic and smart devices, such as mobile phones and tablet computers, and the advent of Web technologies and services, particularly when cloud-enabled, suggest that an integrative EPDM tool may not have to employ traditional computers and user interfaces [49]. Furthermore, the rapid progress in interactive and portable devices and the continuous increase in Internet adoption make them suitable environments for EPDM tools. So, an EPDM tool design must take into account the progress in information and communication technology (ICT).

Accordingly, this active classification parameter *System access* is firstly aimed at illustrating whether the proposed tool from a selected paper is already implemented as a *Deliverable* (E1) (i.e., an existing and effective tool and not a theoretical conception) and, if so, to describe which *Type(s) of system access* (E2) are available to enable the decision makers or other stakeholders to use it. We consider four types of systems access in this classification parameter: Desktop application, Web application, Cloud application, and Mobile application. The definition of such a parameter assumes critical importance to investigate the avail of current strategic EPDM solutions from novel medium access and technologies.

2.3.5. Method(s) used

For any renewable and sustainable energy project to be efficient and successful, a synergy has to be found considering the present resources and the predicted outcomes. Typically, problems-solving in strategic EPDM follow a number of general and successive steps. Firstly, the process incorporates defining the problem, eliciting relevant decision factors, then, identifying strategic actions, and finally evaluating and selecting the action(s) that satisfy the decisions maker's expectations [2,10,54]. For instance, one of the most dominant challenges undertaken in the current literature is the problem of assessing renewable and sustainable energy projects to select the most suitable ones for a given area [41,61,89,106]. Most of the times, the decision has been made through DSSs based on conventional MCDM methods, fuzzy decision-making models or a combination of the two approaches (i.e., FMCDM). DSSs are assumed to (i) increase the decision makers' satisfaction, (ii) enhance the decision-making process, and (iii) improve the quality of communication and collaboration [171]. There are different types of DSSs and each one has had a period of popularity in both research and practice [172]. Over time, DSSs have been categorized mainly according to the type of the approach and technology used for decision support. The most recognized DSSs in the literature are [171–176]:

Data-driven or data-oriented DSSs emphasize access to and manipulation– of large amounts –of internal and sometimes external (company) data. These systems infer decisions by investigating relations or patterns in existing– historical –data, for instance, data warehouses, reporting tools, and executive information systems (EIS).

Model-driven DSSs use mathematical, financial, simulation, and optimization models to enhance the decisions support. These systems require data and parameters provided by decision makers to aid in solving and analyzing a considered decision-making problem. However, they are not necessarily data intensive (i.e., very large data are not needed). Therefore, a DSS based on MCDM, fuzzy, or MOO models is a model-driven DSS.

Communications-driven DSSs facilitate communication, collaboration, and coordination in decision-making situations that require more than one person. For instance, group DSSs (GDSSs) which support a group of decision makers are communications-driven DSSs.

Knowledge-driven DSSs access specialized problem-solving expertise for a particular decision-making problem stored as facts, rules, or/and procedures. Generally, the expertise consists of knowledge originated from domain experts, their perception of the decision-making problems, and appropriate skills for solving these problems. The widespread ESs are knowledge-driven DSSs.

However, some DSSs might belong to more than one type. For instance, DSSs that combine MCDM and GDM models are hybrid (model and communications-driven) DSSs that intend to manage complex multiple criteria group decision-making (MCGDM) problems [16,177]. Moreover, as ICT continues to advance, research in DSSs increases too [178]. In their work [179], Arnott and Pervan tried to cover all the important updates in the DSSs community. They notice the appearance of several new types of DSSs: Web-based DSSs, intelligent DSSs (IDSSs), interactive DSSs, spatial DSSs, geographic information systems (GISs), environmental DSS, forecasting and predictive modeling, BI, big data integration in decision-making processes, etc.

Therefore, this classification parameter (*Method(s) used*) investigates for each selected study the appropriate *Type(s) of the DSS* (F1) (if exists) or/and the proposed *Decision-making approach(es)* (F2) (i.e., MCDM, fuzzy sets, FMCDM, GDM, stochastic models, optimization model, recommender model, mathematical model, hybrid approach, etc.) considered to solve the related-EPDM problems. Moreover, adding this active parameter will certainly facilitate obtaining insights about dominant types of DSSs and the most utilized decision-making approaches in strategic EPDM.

3. Results and in-depth analysis

The representative sample consists on 78 published scientific papers which cover the range of applications to strategic EPDM problems from early 2005 until September 2017 (for the analysis, 19 papers dated 2017 are already available online). A total of 21 articles were excluded even after applying the additional selection criteria (see Section 2.2), three of which belonging to conference proceedings (on the exception of [180]), seven are also deleted because of the unavailability of the full papers, and moreover 11 papers were additionally eliminated due to their unsuitability for the strategic EPDM category (DL1 from Table 1) after carefully screening their full text. As already mentioned, this review will not address studies from the operational decision level of EPDM (DL2 from Table 1). However, three energy management-related articles [181–183] were considered as these papers' contributions match both strategical and operational decision levels, hence, the possibility of their application in various EPDM categories.

An increasing trend of decision-making methods, models, and systems over time is evident supporting the results from the previous literature reviews (see Table 2). In the following paragraphs, results and analysis of the representative sample over the different considered classification's parameters are presented; detailed data referred to each paper are listed in Table 6. The suggested tabular overview permits the reader to quickly derive relevant information about the selected papers. Hence, insights are gathered and analyzed to provide a general view and discussion on (i) major complexities found in classical/traditional strategic EPDM solutions, and (ii) challenges for next-generation EPDM solutions.

EPDM categories and stages. The selected papers cover applications in several strategic EPDM categories ranged over diverse EPDM stages. With regards to the EPDM categories, most of the studies analyzed in the sample (94%) refer to the C1.4-*Energy evaluation and assessment* category, followed by C1.5-*Site selection* (32%), C1.1-*Energy planning* (26%), C1.2-*Energy policy* (17%), and last C1.3-*Environmental impact analysis* (10%). In this context, the first category (C1.1) covers a wide range of important strategic EPDM problematics (e.g., investments [88,189,207], sustainability assessment of energy systems, sources, technologies and options [34,42,93], power generation scenarios [97,205], production pathways [21,105,185], etc.) whereas the remaining categories are more like topic-specific (i.e., site/location, policy, environmental impacts, and strategic planning). Furthermore, considering that strategic EPDM problems are naturally interrelated and consecutive, it is noticed that many papers (47%) cover more than one category (e.g., an MCDM method might be adapted to be utilized for choosing the best RES or for selecting the best sites for RES implementation). On the other hand, the majority of the selected articles refers to the stages: S1-*Planning and initiation* (97%) and S3-*Improvements and restructuring* (73%). Additionally, a great deal of those papers refer to both stages simultaneously (68%) as some decision-making approaches remain applicable for different stages as pointed out by those papers' authors (e.g., classical MCDM methods are suitable for selecting best RES to initiate a project or to later restructure the same project) [14,34,42,93,106]. Nevertheless, the remaining stages S2-*Control and development* and S3-*Benefits and outcomes* received less attention by researchers (13% and 2%, respectively).

Uncertainty types and solutions. The representative sample confirms the necessity of uncertainty handling in strategic EPDM problems. Table 6 shows that 53 articles considered handling one (e.g., [34,93]) or– simultaneously –more than two (e.g., [110,197]) types of uncertainty (see Section 2.3.2). A great deal of these articles (87%) was devoted to deal with one of two types of uncertainty: UT2-*Fuzzy uncertainty* (69%) or UT4-*Unascertained uncertainty* (55%). The higher share over these two types is likely due to the subjectivity and vagueness of stakeholders' (policy and decision makers) judgments and their incapability to provide exact precise values in most strategic EPDM problems [6]. Besides, fuzziness (UT2) and subjectiveness (UT4). The remaining two types of uncertainty, UT1-*Random uncertainty* (e.g., [183,214]) and UT3-*Grey uncertainty* (e.g., [19,88]) are less treated by researchers in strategic EPDM (11% and 16%, respectively).

Therefore, in most case studies, the uncertainties have been handled throughout (1) fuzzy linguistic (38%) or (2) fuzzy (23%) decision-making environments while considering other types of preferences' representation (e.g., intervals [199,215], intuitionistic [111,197], or trapezoidal fuzzy numbers [41]). The remaining articles address uncertainty (mostly in an MCDM context) by carrying out sensitivity analysis (26%), monte carlo simulation (5%), or scenario analysis (3%) of the criteria weighting as a way to check the robustness of the results. Additionally, (fuzzy) cognitive maps are apparently the most used to handle uncertainty due to causal relationships (i.e., UT1) [202,214]. Last, Table 6 reports the use of some other techniques (11%)– as exceptions –to handle some particular situations of energy planning under uncertainty such as interval linear programming [22], cloud theory [114], objective criteria [67], datamining [181], BNs [109], factor screening method [208], real options valuation [210], and risk-aversion optimization [183].

Intelligence integration and components. Table 6 shows that *intelligence* integration in strategic EPDM has been considered in only 10 papers (12%) all over the past 12 years. Hence, to place the focus on this finding, the authors preferred to subdivide the representative sample into three distinct periods: (1) 2005–2010, (2) 2011–2015, and last (3) 2016 and onwards.

In the first 5 years period, two papers [49,104] are the exceptions. Simão et al. [49] proposed a conceptual system framework and a learning environment that supports public participation in collaborative planning. The authors described their implementation, as a proof of concept, in a system for Web-based participatory wind energy planning. On the other hand, Cinar and Kayakutlu [104] described scenarios creation for energy policies using BN models. Additionally, the authors in [104] proposed a decision model to support researchers in forecasting and scenario analysis fields and more importantly to help policy and decision makers to evaluate different energy scenarios aiming the sustainability.

Also, in this period only two papers [24,189] have been identified herein. First, Dagdougui et al. [24] proposed a DSS for the hydrogen exploitation, focusing on some specific planning aspects, in particular, the selection of locations, with high hydrogen production, mainly based on the use of solar and wind energy sources. Moreover, to predict the renewable energy potential that can be assigned to each point of a region, data have been inferred using an ANN algorithm (e.g., to establish a forward/ reverse correspondence between the longitude, latitude, elevation and the mean annual renewable energy and the hydrogen mass). On the other hand, Daim et al. [189] proposed to create and investigate clean energy investment scenarios using the BN. Thus, BN has been used in [189] to handle the complexity of energy investments' scenarios.

Last, this period has been the most remarkable wherein 6 papers are identified [81,109,170,181,203,214]. Firstly, Maté et al. [181] explored the opportunities to adopt more intelligent ways of managing existing RES. The authors [181] proposed to improve energy consumption predictions via integrating internal data already stored in data warehouses together with external big data. In that same direction, Abaei et al. [109] suggested the application of BN and influence diagram to MCDM for improvement of power generation efficiency in renewable and sustainable energy applications.

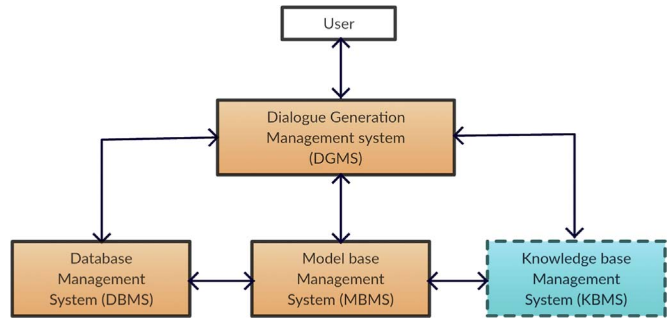

Fig. 2. The basic components of an intelligent and knowledge-based DSS.

Moreover, the proposed methodology has been applied to the decision-making process for marine renewable energy site selection. Ghosh et al. [203] developed an integrated decision-making method that combines ANN and MCDM techniques to predict an index that directly represents the suitability of locations for wave energy generation. Greco et al. [214] suggested to integrate the open innovation paradigm (OIP) in the energy sector to take advantage of external knowledge. The authors [214] stated that this paradigm will certainly help key stakeholders (e.g., utilities, vendors, laboratories, and universities) to improve their innovation performance. Uniquely, Mousavi et al. [81] proposed the only approach computing the relative importance of each energy decision maker or expert during their participation in a GDM renewable energy policy selection problem throughout a hesitant fuzzy modified preferences selection index method. Finally, Mosannenzadeh et al. [170] developed an innovative learning methodology to predict barriers to implementation of smart and sustainable urban energy projects. The proposed methodology as pointed out by the authors is applicable and replicable for planners and decision makers in different territorial levels to facilitate and accelerate the implementation of smart and sustainable energy projects.

System access. Regarding the use of advanced ICTs especially the different available *System access* options (e.g., Web services, cloud platforms, and mobile applications, etc.) to provide policy and decision makers in the energy sector with interactive and user-friendly solutions, the applicability has been moderately proven (15%). In fact, no single decision-making method, model, or system from the selected papers over the last two years proposed the implementation of an effective and deliverable DSS (no matter what is the type of system access). Moreover, only eight papers implemented a desktop application [18,20–23,93,184,192], four papers proposed the Web as a medium support for their contributions [28,30,49,180], and no single study investigated the remaining technologies (i.e., cloud and mobile applications).

Method(s) used In relation to this parameter, the following results are obtained. The majority of studies (76%) proposes to develop a standalone decision-making approach as problem-solving for a specific strategic EPDM problem (e.g., [34,42]) rather than implementing the concept of a complete DSS (17%) such as [18,184]. The remaining studies (2%) are theoretical decision-making frameworks. Regarding types of the selected DSSs, 13 papers (76%) are model-driven (e.g., [21,22]), three are data-driven [18,180,184], two are knowledge-driven [20,170], and another two are communications-driven DSSs [49,192].

The authors noticed that: (i) GISs are widely used as supporting tools (35%), (ii) poor adoption of Web-based DSSs (17%) regarding recent advances in internet and Web technologies, and (ii) most of the

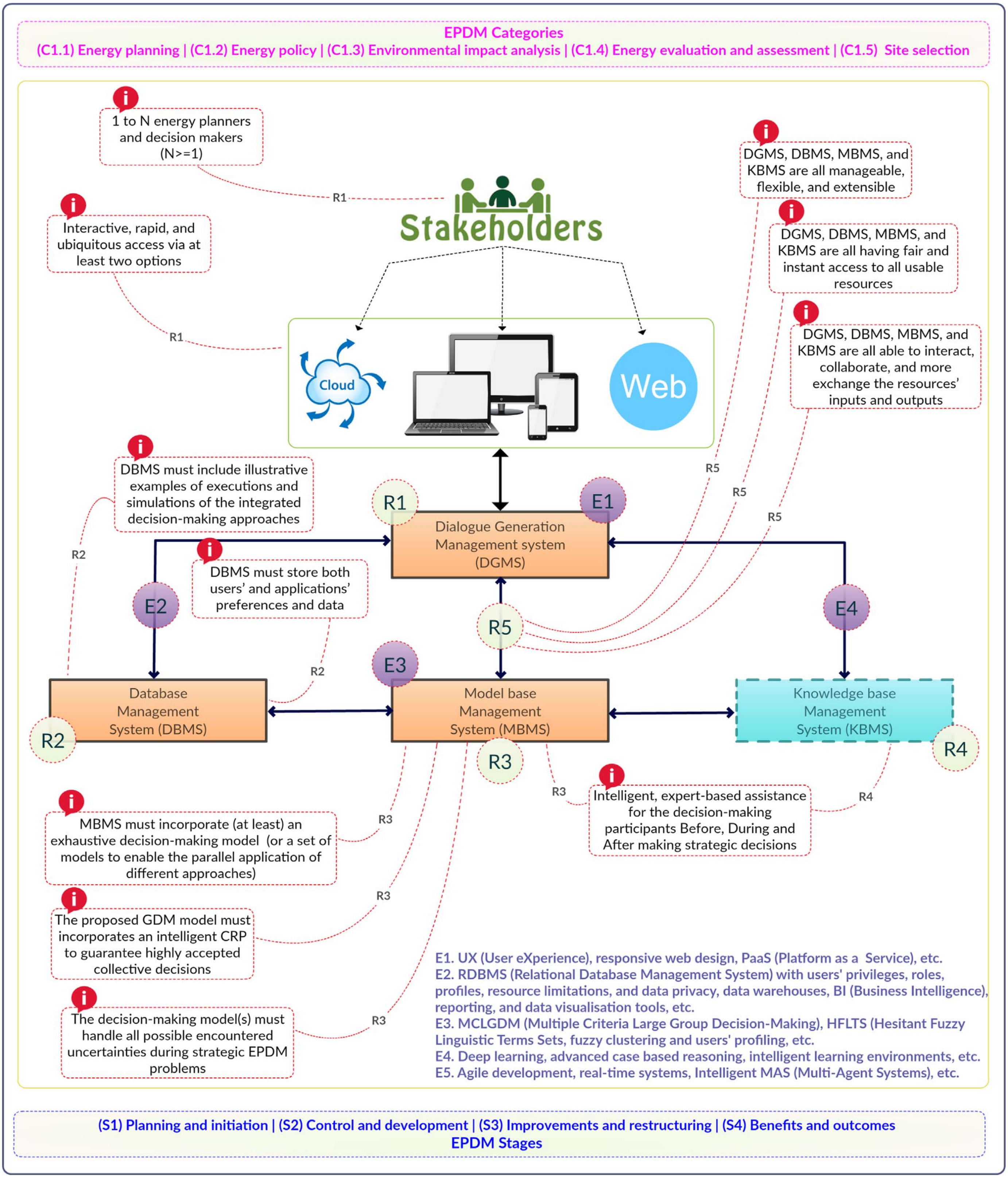

Fig. 3. The extended energy planning decision-making framework.

DSSs (20%) in the representative sample are in the period from 2005 until 2014, whereas only one paper belongs to 2017 [170]. On the other hand, over most dominant decision-making approaches used for decision-making, we mark hybrid approaches (65%) in the form of FMCDM (42%) or the combination of different classical MCDM methods (23%). Thus, standalone MCDM approaches received less attention (26%) especially in the last two years (only six papers from 57). The remaining studies (14%) are using other decision-making approaches such as optimization models [183,199] and scenario-based decision-making [104,187]. Last, GDM models are still scarce (16%) compared to single decision maker approaches (84%) in strategic EPDM problems.

To sum up, the results from this representative sample highlight some new complexities and confirm major ones of existing EPDM solutions in most cited (see Section 2.1) and most recent (see Table 2) literature reviews on this topic. Thus, these reviews' results are used as evidence and support for this review's findings, as follows:

- It was evident that the number of publications dedicated to strategic EPDM solutions has been increased the last decade (R1.AR1, R7.AR3, R8.AR1).[2] The majority considers decision-making approaches that particularly concentrate on some specific EPDM categories (C1.4 and C1.5) or/and stages (S1 and S3).
- Plenty of researchers still employs classical/traditional decision-making approaches in a single decision maker framework (i.e., not a GDM approach) with a markedly high share in the fields of MCDM and fuzzy sets that have been extensively used since the late 1980ss (R1.AR2, R6.AR1, R7.AR1, R8.AR3, R9.AR1). Moreover, the dominant trend in the last decade is the combination of different decision-making methods, since, hybrid MCDM and FMCDM were ranked as the first methods in the literature in use (R1.AR4, R4.AR1, R5.AR1, R6. AR3, R9.AR5).
- Some researchers tried to investigate the use of new fuzzy sets within the MCDM context in order to face typical uncertainty situations (UT2 and UT4) encountered in real-life decision-making problems (R5.AR4). Regarding this, the particular shift towards analyzing strategic EPDM problems in fuzzy linguistic environments has been strongly noticed (R1.AR5). The remaining two types of uncertainty (UT1 and UT3), are less treated by researchers in this field.
- Apparently, ISs, in general, and DSSs, in particular, received less attention in strategic EPDM, especially in the last two years. The majority of the proposed approaches are mainly decision-making methods or models (i.e., not complete DSSs). Except for some few attempts to explore potentials of the model and data-driven DSSs, a clear absence of the remaining types has been noticed (i.e., knowledge and communications-driven).
- The transition towards RES has affected concerned researchers in this field (especially from 2016 and onwards). Nowadays, researchers attempt to figure out intelligent and innovative decision-making approaches in order to support optimization of the technologies involved in the renewable energy market and achieve a better efficiency and costs reduction. For instance, some researchers recently investigated the usefulness and potential applications of unusual approaches in renewable and sustainable energy planning such as BNs, ANNs, and ML algorithms (R2. AR1, R2. AR2, R2. AR3, R3. AR2). Although, efforts towards the integration of new intelligent components in strategic energy planning are still scarce.
- Last, a few attempts over the last decade were identified to be partially like interactive and user-friendly EPDM solutions hence adequately supporting policy and decision makers in the energy sector. In fact, no single decision-making method, model, or system from the selected papers over the last two years proposed to implement a complete deliverable tool (no matter what is the type of system access). Furthermore, no single study investigated more recent technologies such as mobile and cloud-enabled applications.

Identification of "quality indexes" The major complexities, weaknesses, and limitations of currently available strategic EPDM solutions identified during the review in addition to most important elements to be considered as "quality indexes" of next-generation solutions are given in Table 7. Additionally, outlined challenges for next-generation EPDM solutions from most recent (see Table 2) literature reviews are used as evidence and support for this paper's statements as follows:

Classical/traditional strategic EPDM solutions in the best scenario (i) cover two EPDM categories and stages and at most handle three types of uncertainties using classical treatments; (ii) give less attention to intelligence integration in decision-making processes and at best use old-fashioned AI techniques or classical ML algorithms; (iii) neglect recent advances in modern system access technologies, refer to standalone/hybrid decision-making methods/models, and in best cases implement a model-driven DSS; and last (iv) manage the complex nature of real-life EPDM problems (R6.AC5, R6.AC6, R7.AC1)[3]– due to the presence of interrelated perspectives, conflicting objectives, and (a large number of) involved stakeholders with different aims and preferences [15,16] –using classical GDM models.[4] In this sense, the planners and decision makers (often) are not fully aware of the range of factors involved, the implications of the other participants, and more importantly the hidden sensitive details that require deeper investigations and might completely change and affect the final decisions made once omitted (R9.AC2). It is sometimes not until after generating a proposed action that unforeseen consequences become perceptible or evident and that a reconsideration of the whole decision-making process that generated this decision becomes necessary [49]. Importantly, these solutions usually provide final decisions or recommended actions without deeply examining the relationship between these and the existing decision parameters (participants, alternatives, and criteria), and without providing comprehensive explanations for results (R4.AC2, R5.AC1, R6.AC3, R9.AC1). Therefore, they are not "intelligent" enough to: (i) identify and analyze the relationships between initial inputs, participants profiles, and obtained outputs, (ii) provide logical interpretations and rational assumptions from the outputs, and (iii) extract additional knowledge from the decision-making process (R7.AC4). These solutions are, by contrast, completely data-driven (i.e. sufficiently sample data are required to estimate the final decisions) [48].

Alternatively, next-generation strategic EPDM solutions need to offer planners and decision makers the right tools to cover all existing EPDM categories and stages (R6.AC4). These tools must be intelligent, interactive, and extensible[5] hybrid DSSs with at least Web and mobile applications' capabilities (R1.AC4, R1.AC5, R4.AC3, R4.AC4, R6.AC2, R7.AC2, R7.AC5,R8.AC3). Firstly, intelligence is a crucial decision support aspect that must be enabled considering advances in AI/ML algorithms, intelligent knowledge management and ESs, and innovative data mining techniques [217]. Furthermore, such DSSs need to

[2] For instance, R1.AR1 refers to Review 1 [1] and Authors' result 1 from Table 2.

[3] For instance, R6.AC5 refers to Review 6 [54] and Authors' conclusion 5 from Table 2.

[4] Regardless of the approach considered, the traditional selection process for reaching a solution to GDM problems is made up by two phases: (i) an aggregation phase, in which preferences of experts are combined by using an aggregation operator, and (ii) an exploitation phase, where a selection criterion is applied to obtain an alternative or subset of them as the solution for the problem [216].

[5] The DSS must be designed to be flexible so it could be reconfigured to support a broad selection of categories, stages, and decision makers, involved in EPDM.

treat all possible encountered uncertainties during strategic EPDM problems including fuzziness, subjectiveness, vagueness, causal factors, unclear, missing, and unavailable information. Hence, they should intelligently reason over the unknown, incomplete, and conflicting information from decision makers [81,218]. In this sense, automatized assistance from domain experts in the form of knowledge bases [219] (during the complete decision-making process), combinations of different classical uncertainty solutions, and exploration of new fuzzy sets [220–222] might be of great use for interested researchers (R1.AC4, R1.AC5, R5.AC2, R5.AC3, R5.AC4, R5. AC5, R6.AC7). Moreover, future solutions need to consider advances in GDM and consensus reaching process (CRP)[6] [224–227] (R9.AC3). Thus, these solutions need to (i) identify and analyze the relationships between initial inputs, participants profiles, and obtained outputs, (ii) provide rational assumptions and logical interpretations of the outputs (R8.AC6), and (iii) extract additional knowledge from the undertaking decision-making process [169].

Considering all the above "quality indexes" and examining the results of the review, only nine papers [49,109,167,170,181,192,203,206,215] were deemed appropriate (where the authors differently addressed some EPDM problems that have been classically or not solved at all by the community), despite one of them are more energy management oriented solution [181] and none of them exactly satisfies all (or at least 50%) the above requirements.

Firstly, in only two of these articles the authors proposed a DSS [49,170], one is a computerized tool [192], instead the rest is standalone decision-making approaches or theoretical decision-making frameworks [109,167,181,203,206,215]. Besides, in Simão et al. [49] even if a hybrid Web-based multiple criteria DSS (interactive, data, model, communications, and knowledge-driven) is proposed– to support public participation in distributed collaborative planning using a learning environment –the authors covered only two strategic EPDM categories (at best C1.4 and C1.5) and two stages (at best S1 and S3), nor considered components to deal with encountered uncertainty situations in such complex participatory decision-making problems. In contrast, even if the authors from [170] stated that their DSS can be extended to other EPDM topics (categories and stages), in its current form, the proposed solution is still far away from satisfying the minimum requirements in next-generation EPDM solutions (e.g., no system access or uncertainty handling). Same to be noticed about [192] where an interactive computer tool (Desktop application) is proposed to help non-experts make informed decisions about the challenges faced in achieving a low-carbon energy future.

Hence, the most innovative standalone decision-making approaches can be ascribed to the following papers [109,167,181,203,206,215]: Öztayşi and Kahraman [167] proposed one of the first attempt that investigated the use of different and recent fuzzy sets (interval type-2 and hesitant fuzzy sets) in a strategic EPDM problem (C1.4); Abaei et al. [109] and Ghosh et al. [203] proposed one of the most innovative decision-making approaches to solve site selection problems (C1.5), using BN and influence diagram, and ANNs, respectively; Maté et al. [181] proposed advanced data analytics tools (energy consumption behaviors using data mining and big data), predictive AI models (ANNs), and an innovative knowledge management using an information extraction system (even if it is not 100% strategic EPDM oriented study); whereas, Gitinavard et al. [215] is the only attempt to handle partially and completely unknown criteria weights information while combining multiple classical uncertainty solutions (fuzzy environment and sensitivity analysis). However, each of them presents some limitations: while the first four [109,167,181,203] present apparently single decision maker models with limited capabilities to handle all types of uncertainty, the remaining paper [215] presents a classical GDM model where an aggregation approach is applied to combine the preferences of different decision makers resulting information loss and distortion (caused by unifying heterogeneous information) [227].

4. Towards next-generation strategic EPDM solutions: an extended expert-based framework for intelligent decision support

This section focuses on the development of a theoretical framework towards effectively activating next-generation EPDM solutions for enhanced, sustainability-oriented energy planning. The proposed framework is an original result coming from the "quality indexes" identified through the review process (see Section 3).

In order to guarantee practicality of a next-generation strategic EPDM solution, the later should be capable of responding to the fast trends and changes in renewable and sustainable energy market/technologies whilst resolving the complex strategic energy planning problems as identified in this review. In this sense, even though the use of a next-generation strategic EPDM solution will be straightforward for most of the potential stakeholders (due to the potential adoption of user-friendly solutions), its use for real-life EPDM situations is challenging and needs further discussion. Moreover, it is hard enough to state that a single DSS may resolve all the complexities and challenges discussed during this review and might cover all strategic EPDM categories and stages. This sounds reasonable if– only –a progressive and agile approach[7] [229,230] is considered to develop the DSS, resulting in an integrated and extensible strategic EPDM solution using modules and sub-modules (each with a specific use) [231]. In this regard, a theoretical framework is developed to support researchers towards adopting next-generation EPDM solutions by extending the basic structure of an intelligent and knowledge-based DSS to incorporate the "quality indexes" identified through the review process.

The basic building blocks of a typical DSS were first proposed in [173] as follows:

- The *database management system* (DBMS) includes all mechanisms that ensure coherence of the needed information and the required data to execute the analysis of the problem at hand.
- The *model base management system* (MBMS) is responsible for the treatment of the model base[8] including its storage, retrieval, update, and adjustment.
- The *dialogue generation management system* (DGMS) is specifically designed to manage communications between the end-users and the developed DSS.

By integrating an additional fourth component, the *knowledge base management system* (KBMS) with AI and ES techniques as shown in Fig. 2, an intelligent and knowledge-based DSS (commonly known as IDSS) can be created to support decision-making with expert-level qualities [174–176]. Basically, these systems incorporate an ES that receives inputs from the DGMS and DBMS, evaluates them, and

[6] In any decision process, it is preferable that the decision makers reach a high degree of consensus on the solution set of alternatives. Thus, the CRP is a dynamic and iterative process for improving and maximizing the degree of consensus or agreement between the set of decision makers on the solution alternatives in GDM [16,223].

[7] Agile software development advocates adaptive planning, evolutionary development, early delivery, and continuous improvement, and it encourages rapid and flexible response to change [228].

[8] The model base is a collection of decision analysis models, used to support the decision-making process.

provides recommendations to users via the DGMS [232]. Therefore, IDSSs are results of combining basic function models of typical DSSs with the knowledge reasoning techniques of AI to generate knowledge for decision-making support, guide users through some of the decision-making phases, supply new capabilities, offer advice on specific problems tasks, and explain conclusions and recommendations [173–176].

Apparently, incorporating knowledge bases and AI techniques in decision-making processes had different benefits. However, with the exception of some few attempts [20,170], IDSSs received less attention in strategic EPDM even if these systems are dated for more than three decades. Moreover, the incorporation of knowledge bases with classical AI techniques deemed insufficient to cover all the identified “quality indexes” as identified in this literature review. Hence, there is an emergent need for an extensible and complete solution that will potentially cover all categories and stages of strategic EPDM (as explained in Section 3). This paper's authors extended the basic structure of an IDSS and alternatively proposed important features and additions to be considered for next-generation EPDM solutions as shown in Fig. 3. The objective of this study is to (i) provide the guidelines, suggestions, and necessary components to be largely considered in next-generation strategic EPDM solutions, (ii) enhance the understanding of real-life differences between classical/traditional and next-generation solutions, hence, (iii) demonstrate the proof of concept for the proposed extended framework. So, practitioners and interested researchers in this area of research need to fulfill the following requirements in their future implementations (depending on the final systems' objectives) to be referred as next-generation EPDM solutions:

*R*1. The DGMS must enable communication, discussion, and participation of 1–*N* energy planners and decision makers (governments, investors, regulators, consumers, interest groups, etc.) (with $N \geq 1$). Moreover, the DGMS should provide interactive, rapid, ubiquitous access for the involved decision makers to the strategic EPDM solution and its features via at least two options[9]: Web or cloud-enabled platform and a mobile application, which means that standalone solutions are no longer suitable in this framework [231]. Moreover, when considering a GDM context, mobile applications will certainly facilitate the mobilization of knowledge, giving the users the possibility to get support through their mobile devices regardless of the time and location [233];

*R*2. Regarding the (possible) distributed nature of the participants in strategic EPDM, their heterogeneity, and the ubiquity constraint imposed in this framework, the DBMS must store both users' and applications' preferences and data. On the one hand, the *Applications' data* refer to past and undergoing decision-making processes' information and– inputs/outputs –decision parameters (e.g., alternatives, criteria, participants, results, etc.) that concern effective or potential sustainable and renewable energy projects (including important information such as investments, partners, objectives, past and current situation of the project, etc.), policies, scenarios, and so on. In addition, information related to the different available system access options (e.g., look and feel, customization settings, etc.) are also stored. On the other hand, the *Users' data* concern decision makers' participations, preferences, feedbacks, in addition to their personal data (profile). The two proposed components will certainly ensure the extensibility and re-usability feature in strategic EPDM solutions via facilitating technologies' migration and updates, and more importantly enabling the possibility of investigating (unlimited number of) future EPDM categories, stages, and problems. Additionally, the DBMS must include illustrative examples of executions and simulations of the integrated decision-making approaches to assist newly users to get familiarized with the proposed solution. This might be of great use for academicians too in order to compare results– based on the illustrative examples –obtained from different decision-making approaches [56].

*R*3. The MBMS must incorporate (at least) an exhaustive decision-making model (or a set of models to enable the parallel application of different approaches and to understand the robustness of findings in the different decision-making models [52]) capable of:

1. Dealing with both single (N=1) and GDM (otherwise) situations. In a case where $N \geq 2$ it is mandatory that the proposed GDM model incorporates an intelligent CRP to guarantee highly accepted collective decisions. Firstly, a bespoke feedback mechanism is necessary to help in achieving the consensus [16]. Moreover, the CRP must take into consideration the heterogeneity concern in (large) GDM problems hence inadequate participants' profiles (in term of reliability and confidence), and knowledge levels differences. Thus, the considered decision-making model must deal with these real-life complexities which is not the case in existing classical/traditional strategic (GDM) EPDM solutions as identified during this review. Last, in a case where different decision-making models are considered, the development of linkages between these models is mandatory (to ensure the possibility of using two or more distinct models as a hybrid approach) [52].
2. Handling all possible encountered uncertainties during strategic EPDM problems including fuzziness, subjectiveness, vagueness, causal factors, unclear, missing, and unavailable information. Additionally, the proposed model must intelligently reason over the unknown, incomplete, and conflicting information from decision makers [81,218]. Thus, the model must incorporate different uncertainty solutions simultaneously or/and explore the applications of more recent and efficient ways to handle the different types of uncertainty (see Section 2.3.2). Moreover, the authors propose an automatized assistance from domain experts in the form of knowledge bases [219] to support decision makers during the complete decision-making process (see *R*4).

*R*4. In the extended framework (Fig. 3), the authors suggest the use of the KBMS as intelligent, expert-based assistance for the decision-making participants *Before*, *During* and *After* making strategic decisions [169]. Apparently, this is not the case within existing ESs that generally used entirely *During* the decision-making process (i.e., in regular scenarios the inference engine applies the rules in the knowledge base to the known facts to deduce new facts) [174–176]. In real-life strategic EPDM problems, planners often are not fully aware of the (i) range of factors involved, (ii) implications of the other participants, and more importantly (iii) hidden aspects that require deeper investigations and might completely change and affect the final decisions made [169,170]. It is sometimes not until after generating a proposed action that unforeseen consequences become perceptible or evident and that a reconsideration of the whole decision-making process that generated this decision becomes necessary [49]. For instance, let us consider a real-life scenario of initiating a renewable and sustainable energy project for power generation, where the involved energy planners (or decision makers) must consider the numerous ecological, socio-economical, and political energy related-constraints *Before*, *During*, and *After* answering the (i) how (the best policy/strategy

[9] It is preferred to combine a Web or cloud-enabled solution within a mobile application to give more accessibility and mobility to the different involved stakeholders.

to consider to attain the target objectives), (ii) where (the project's location), and (iii) what (the most suitable renewable energy technologies) strategic questions. There might happen that: the planners already decided on the site location of the project without considering an important, deeper, and usually hidden concern such as "social acceptance" of the project in that location; or sometimes, due to their limited knowledge, the planners are often incapable of providing precise assessment values when evaluating the renewable energy technologies' efficiency or environmental impacts. Thus, the planners need domain-experts assistance (consultation, support, and validation) [169] before problem identification phase and even more importantly after problem-solving phase. To the authors' knowledge, as it was confirmed in this review, and based on the results and conclusions from most cited and recent literature reviews in strategic EPDM, the described intelligent, expert-based (computerized) assistance has not been proposed in existing classical/traditional strategic EPDM solutions.

*R*5. Last, it is important to ensure that the four components (DGMS, DBMS, MBMS, and KBMS) are all:

1. Adequately manageable, flexible, and more importantly *extensible* (e.g., using the strategy of modules and sub-modules) assuring the later modifications and additions in next-generation EPDM solutions to enable future inclusions of other EPDM categories and stages, or widespread EPDM problems (e.g., from local to national or from national to regional energy planning problems, etc.) [54];
2. Adequately having fair (depending on the decision-making process's priorities) and instant access to all usable resources (database, model base, knowledge base, etc.);
3. Adequately able to interact, collaborate, and more importantly exchange those resources' inputs and outputs. For instance, in *R*3, the MBMS and KBMS need to share (a) input model(s) data from decision makers (e.g., decision makers' evaluations of the set of alternatives) and (b) output knowledge base(s) data from experts (e.g., in the form of fuzzy [234] or belief [48], rule bases [159]) in order to collaborate/communicate to effectively solve the heterogeneity concern in (large) GDM problems (e.g., via applying consistency check to (a) using (b) [235–237]) as explained earlier.

Finally, the proposed framework is exhaustively capable of solving strategic EPDM problems related to different categories or/and stages, if– only –a progressive and agile approach (as already pointed) [229,230] is considered to develop future strategic EPDM solutions [231]. Thus, the authors annotated the proposed theoretical framework (Fig. 3) to facilitate its reading and adoption alongside with possible interconnections between the different components, and some literature techniques (*E*1, *E*2, *E*3, *E*4, and *E*5) that might facilitate satisfying the above-mentioned requirements.

5. Conclusions

The present study constitutes a representative sample of the papers related to the examined research field. A total number of 78 published articles– from 2005 and onwards where 19 papers dated 2017 –was considered. 17 peer-reviewed (renewable) energy and computer science journals discuss and highlight limitations and complexities of existing strategic EPDM solution. This review presents interesting results that can be useful for researchers in decision science and renewable and sustainable energy planning. The analysis was based on a classification specially developed by holistically harmonizing important domain parameters (*EPDM categor(y/ies)*, *EPDM stage(s)*, *Uncertainty handling*, *Intelligence*, *System access*, and *Used Method(s)*) to facilitate investigating the selected solutions' strengths, weaknesses, and more importantly their suitability to handle different aspects in strategic EPDM.

Not surprisingly the number of publications related to strategic EPDM have been significantly increased the last decade. The transition towards RES has affected interested researchers, who try to take benefits from the available knowledge in decision-making to improve the strategic EPDM processes. However, this literature review has shown that existing strategic EPDM solutions are classical/traditional. In the best scenario, they: (i) cover two EPDM categories and stages and at most handle three types of uncertainties using classical treatments, (ii) give less attention to intelligence integration in decision-making processes and at best use old-fashioned AI techniques or classical ML algorithms, (iii) neglect recent advances in modern system access technologies, refer to standalone/hybrid decision-making methods/models, and in best cases implement a model-driven DSS, and finally (iv) manage the complex nature of real-life EPDM problems using classical GDM models. Consequently, the planners and decision makers (often) are not fully aware of the range of factors involved, the implications of the other participants, and more importantly the hidden sensitive details that require deeper investigations and might completely change and affect the final decisions once omitted. Therefore, they are not "intelligent" enough to handle the complexity nature of strategic EPDM problems.

Alternatively, the authors identified a set of "quality indexes" as challenges for next-generation strategic EPDM solutions to offer planners and decision makers the right tools to cover all existing EPDM categories and stages. These tools must be intelligent, interactive, and extensible. Furthermore, such solutions must handle possible uncertainties present during strategic EPDM problems including fuzziness, subjectiveness, vagueness, causal factors, unclear, missing, and unavailable information. Hence, they should intelligently reason over the unknown, incomplete, and conflicting information from decision makers. Moreover, future solutions need to consider advances in GDM and CRP [224–227]. Thus, these solutions need to (i) identify and analyze the relationships between initial inputs, participants profiles, and obtained outputs, (ii) provide rational assumptions and logical interpretations of the outputs, and (iii) extract additional knowledge from the undertaking decision-making process.

As an original result coming from the "quality indexes" identified through the review process, an intelligent and expert-based framework for next-generation EPDM solutions is developed for enhanced renewable and sustainable energy planning. The proposed framework is a brainstorming attempt to orient the EPDM research community to get fully involved towards activating this paper's future vision of more interactive and intelligent next-generation strategic EPDM solutions as it is the case within other disciplines such as (intelligent sustainable) manufacturing and *Industry 4.0* [238,239], (green) supply chain management [240,241], and more significantly in (participative and intelligent) healthcare and medical decision support [242,243]. Thus, all involved energy planning stakeholders' are expected to express their feedbacks, agreements/disagreements, and more importantly their concerns for enhanced, sustainability-oriented strategic EPDM.

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